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Original Research

Unraveling the Channels of Food Security of the Households in Northern Kenya: Evidence from an Exclusive Dataset

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A B S T R A C T

Background: Most of the 10 million Kenyans lacking food security lived in the arid and semi-arid northern part of the country in a climatic condition of high temperatures and very little rainfall throughout the year. Frequent droughts had devastating effects on the livelihoods and food availability of the population.

Objectives: The objective of this study was to assess the food security status of the households in Northern Kenya and examine the factors contributing to their food security.

Methods: De-identified secondary data were used from the 2015 Feed the Future household survey conducted in 9 counties of Northern Kenya. The experience-based indicator of food security was derived from the 6-item Household Food Security Survey Module (HFSSM), which categorized sample households into 3 groups: food secure, having low food security, and having very low food security. An ordered probit model and machine learning algorithm, namely ordered random forest, were used to find the most important determinants of food security.

Results: Findings suggest that the daily per capita food expenditure, level of education of the household head, and durable asset ownership are the key predictors of food security. Households living in rural areas were likely to have low food security, but their probability of being food secure increased with at least primary education and livestock ownership, thus reflecting the importance of education and livestock production among rural communities in Northern Kenya. Access to improved water and participation in food security programs were found to be more important for food security among rural households than they were for urban households.

Conclusions: These results implied that long-term policies on improving access to education, livestock ownership, and improved water may shape the food security status of rural households in Northern Kenya.

Keywords: food security, rural, Kenya, ordered probit, ordered random forest

Introduction

This study aimed to analyze the food security status of households in Northern Kenya and find the factors contributing to their food security using data obtained by a household survey. The motivation for the study comes from Barrett [1] who warns that food security would be a great challenge for sub-Saharan Africa (SSA) in the coming decades given the observed growth in population, income, and urbanization in the region. Africa is home to the most undernourished people where at least 1 in every 4 people is undernourished [2]. About a third of the undernourished people in the world live in SSA [3], and the Global Hunger Index (GHI) is still the highest in SSA compared to that of other regions in the world [4]. Earlier studies documented that an increase in the cost of food, climate change, extreme weather events, and political and social instability threaten food security in SSA [5]. In Kenya, for instance, about 10 million people chronically lack food security and experience poor nutrition, while about 2 million children were estimated to be stunted [6]. The availability of food and

Abbreviations: AG, accelerated growth; FAO, Food and Agriculture Organization; FEEDBACK, feedback segment of the Feed the Future project; FS, food security; FTF, feed the future; GHI, Global Hunger Index; HFSSM, Household Food Security Survey Module; IR, improving resilience; ORF, ordered random forest; REGAL, Resilience and Economic Growth in Arid Lands; SSA, sub-Saharan Africa; UNICEF, United Nations International Children's Emergency Fund; USAID, US Agency for International Development; WFP, World Food Program; WHO, World Health Organization; ZOI, zone of influence.

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key staple food per capita has been decreasing in Kenya, leading to a fall below the recommended 2,250 calorie intake per day for an active adult, and about 10 million people face severe hunger [6]. The issue is particularly acute in Northern Kenya because most of the people in Kenya with low food security live in the arid and semi-arid northern part of the country in a climatic condition of high temperatures and very little rainfall throughout the year. With scarce arable lands, pastoralism and agropastoralism are the main livelihoods of the rural communities in Northern Kenya. Lack of agricultural diversity and frequent droughts have devastating effects on the livelihoods and food availability of the population. As a part of policy research, this article exclusively focuses on food security aspects in Northern Kenya.

Although not exactly in Northern Kenya, there have been many studies that concentrated on household food security. Two lines of studies are relevant to this research: the definition of food security and the predictors of household food security.

The definition of food security can be extracted from the Food and Agriculture Organization (FAO) of the United Nations, stating that food security exists when "all people, at all times, have physical and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life" [7]. The 1996 Rome Declaration on global food security emphasized 3 pillars of food security: utilization, access, and availability. In 2009, stability was added as the fourth dimension of food security [8]. Under this definition, food security is a major and growing problem in the world despite considerable efforts toward zero hunger. Between 2014 and 2019, the number of undernourished people increased by 60 million [1]. Lack of enough food leads to a number of problems including sickness, low productivity, poor performance of children at school, and mental health issues [8,9]. Thus, food security is a complex measure, and multiple attempts have been made to comprehensively capture different dimensions of food security. The extended version uses an 18-item household food security survey module (HFSSM) where the experience of food access, food availability, dietary diversity, and the affordability of a balanced meal is recorded, often using a recall method, along with the allocational trade-offs between adult and children [10-13]. The use of the 18-item HFSSM has shown stability, robustness, and reliability as a measuring tool for household food security status, although it could not be adopted where resources and time are limiting factors [14]. Some researchers reduced the number of items to 15 to 8, focusing more on food intake, depletion, anxiety, and coping strategies [15-19]. The US National Center for Health Statistics proposed a parsimonious 6-item survey module that emphasizes access to food and is used when the 18-item HFSSM cannot be used owing to limited resources or access to information. Blumberg et al. [20] found this approach to be robust when classifying food security in the general population because it identifies food secure households with minimum bias and high accuracy (approximately at the 97.7% accuracy level). The 6-item module is commonly used in the current literature across disciplines [21-24]. This article uses the 6-item module for parsimony, as described in the data section.

The second line of literature discovers the predictors of food security. In general, survey responses to the above-discussed modules, regardless of their item numbers, are aggregated to generate binary or ordinal food security scales, for example, very low food secure, low food secure, and food secure households. Studies commonly used socioeconomic and demographic characteristics of the subjects such as age, sex, marital status, household size, number of children, housing status, location, education level, employment status, income, and expenditure, as the explanatory variables to food security in their empirical models [10,25,26]. Many studies conducted in other countries find that urban households with fewer members and households with older, male, and educated heads are more likely to be food secure than their comparable counterparts [10,19,27-31]. Few studies add behavioral factors such as financial literacy and management [10,12], mental health [22], and dietary intake and diversity [19,32]. However, these predictors often correlate with income and location. An increase in income is expected to be positively associated with food purchase and food security; but income is often vulnerable to measurement errors and misreporting, so a popular alternative is to include food expenditure in the analysis [19,33]. Stable income may reflect in asset accumulation, such as land or livestock ownership. Both assets and livestock ownership were found to be predictors of food security, especially for rural households [28-30,34-37]. Another important predictor can be the access to improved water, that is, piped water into the yard, public tap/standpipe, tube well, borehole, protected dug water, and collected rainwater, because lack of access to safe drinking water may affect cooking and meal intake practices [36,38,39].

This article offers 2 major contributions to the aforementioned literature. First, to the best of our knowledge, this is the first study that uses comprehensive data to identify the determinants of food security in Northern Kenyan households. While Barrett [1] emphasizes paying more attention to the food security of the people in Africa and Gundersen and Garasky [12] point out that reduction in hunger and improving food security require in-depth knowledge about the influencing factors, the findings of this research contribute to the knowledge base. Second, it uses both econometric and machine learning models to find the important predictors of food security. The machine learning model uses a tree-based algorithm to relax the linearity and parametric assumption common in the aforementioned studies. A fundamental strength of machine learning is data-driven feature selection, which is obtained after normalizing and decorrelating the predictors. Given the considerable association between the predictors discussed earlier, the model parsimoniously selects the predictors that define the features of food secure households. Our findings and policy implications would be helpful for the formulation of effective food security programs and policies to combat chronic hunger and malnutrition in places similar to Northern Kenya.

Methods and Data

Theoretical framework

The factors that influence household food security can be derived from the household utility model delineated by Becker [40]. Given the socioeconomic characteristics, households derive utility from consumption and leisure, whereas their consumption bundle includes both food and nonfood items. Many households in developing countries are involved in food production, and they commonly consume a portion of the food they produce at their farm or home, while they sell the rest of the production in the market. Moreover, households purchase other food and nonfood items from the market. Thus, a typical household's utility function can be represented as follows:

$$U_i = f(F_i^{sp}, F_i^{mp}, NF_i, l_i \mid X_i), \tag{1}$$

where U_i is the utility of the household i, F_i^{sp} is the household's consumption of self-produced food, F_i^{mp} is the household's consumption of foods that are purchased from the market, NF_i is the household's consumption of nonfood items that are purchased from the market, l_i is the household's time devoted to leisure, and X_i is a vector of the household's socioeconomic and demographic characteristics.

The household maximizes utility subject to its production, income, and time constraints. According to Strauss [41], households that produce food and consume a part of it make the production and consumption decisions separately. In particular, those households make the production decisions first by allocating time between work and leisure and then allocate the income between consumption of other food and nonfood items [34,41]. Following Singh et al. [42], the household's production constraint can be specified as follows:

$$f\left(Q^{sp}, L, A^0, K^0\right) = 0, \tag{2}$$

where, Q^{sp} is the self-produced food, A^0 is the farm size, K^0 is the fixed capital stock, and L is the total labor used in the production. We assume that the production function in Equation *2* is convex and twice differentiable—increasing in outputs and decreasing in inputs.

The household earns income from selling a part of its own-produced food items and may have additional nonfarm income. Both types of income are used to purchase other food and nonfood items from the market and for hiring labor from the market for farm production. In addition, the household may use family labor on the farm. Thus, the household's income constraint can be given as follows:

$$P^{sp}(Q^{sp} - F^{sp}) - P^{mp}F^{mp} - P^{nf}NF_i - w\left(L - l_f\right) + N = 0 \tag{3}$$

where, P^{sp} is the per-unit market price of the food item produced by the household, $(Q^{sp} - F^{sp})$ is the quantity of self-produced food that the household sells in the market, P^{mp} is the price of market-purchased food products, P^{nf} is the price of market-purchased nonfood items, w is the market wage rate, L is the total labor units that the household uses to produce food, l_f is the total family labor units the household use to produce food, and N is the household's off-farm income. We assume that the household entirely spends the sum of all income. Furthermore, the household's time constraint can be expressed as follows:

$$T = l_f + l, \tag{4}$$

where, T is the time endowment that the household spends working on the farm l_f and leisure l. Substituting Equation *4* into Equation *3* and rearranging, we have the household's constraint as follows:

$$P^{sp}Q^{sp} + wT + N - wL = P^{sp}F_i^{sp} + P^{mp}F^{mp} + P^{nf}NF_i + wl \tag{5}$$

The household's demand for food can be derived by solving the first-order conditions of the utility maximization problem given the utility function in Equation *1* subject to the income and time constraints that are combined in Equation *5*:

$$F_i = f\left(P^{sp}, P^{mp}, P^{nf}, w, Y^*\left(P^{sp}, w, A^0, K^0, N\right) \mid X_i\right) \tag{6}$$

where, F_i is the quantity of food demanded by household i, which is a function of the prices of food and nonfood items that the household consumes, w is the market wage rate, and the household's optimal income, Y^*, which depends on the market prices, wage rate, farm size, capital stock, and nonfarm income. Empirically, when market prices and wage information are not available or cannot be used, a widely adopted approach is to use a reduced form of Equation *6* to estimate household food demand.

Empirical model

According to Greene [43], there is a continuum of different strengths of preference associated with different individuals, and their derived utility ranges on the real number line on a discrete scale as $-\infty < U_i^* < \infty$. The continuous range of preference can be divided by censoring the continuum of utility to map the segments to the household's food security status. Thus, the observable ratings indicate a censored true preference.

Following the above-discussed literature, let us assume 3 ordered measures of household food security: very low food security indicated by a numeric value of 0; low food security indicated by a value of 1; and food security indicated by a value of 2. To map these 3 food security levels, we divide the utility continuum into 3 discrete ranges using 2 thresholds: α_1 and α_2. Letting FS_i denote the food security status of the ith household with $v = \{0, 1, 2\}$ level of food security, then U_i^* can be mapped to FS_i as follows:

$$FS_i = \begin{cases} 0 \text{ if } -\infty < U_i^* \le \alpha_1 \\ 1 \text{ if } \alpha_1 < U_i^* \le \alpha_2 \\ 2 \text{ if } \alpha_2 < U_i^* < \infty \end{cases} \tag{7}$$

In the absence of market prices and wage information, U_i^* can be expressed as a linear function of observable household characteristics and unobserved idiosyncrasies [16]. Denoting households' socioeconomic and demographic characteristics by a vector X_i and unobserved idiosyncrasies by ϵ_i, the linear form of the derived utility is given by the following:

$$U_i^* = X_i'\beta + \epsilon_i. \tag{8}$$

where the unobserved term in Equation *8* has an unknown distribution $F(\epsilon_i)$. The probability of ith household having a food security level $v = \{1, 2, 3\}$ and utility threshold α_j (where $j = 1$, 2) can be expressed as follows:

$$Prob(FS_i = v | X_i)$$

$$= Prob\left[\alpha_{j-1} - X_i'\beta < \epsilon_i \le \alpha_j - X_i'\beta\right]$$

$$= F\left(\alpha_j - X_i'\beta\right) - F\left(\alpha_{j-1} - X_i'\beta\right) \tag{9}$$

One needs to know the exact distribution of $F(\epsilon_i)$ to derive the probability. Three attempts were made to address this problem. First, ϵ_i can be assumed to be normally distributed ($F = \Phi$) with zero mean and a constant variance. Then, the probability can be estimated using an ordered probit model. Second, assuming a standard logistic distribution for ϵ_i with variance $\frac{\pi^2}{3}$ gives the ordered logit model. Third, a tree-based machine learning model, such as, ordered random forest (ORF), drops the parametric assumption on ϵ_i and the linearity assumption on Equation *8*, and finds the relative weights of predictors through iteratively minimizing the prediction errors. The probit specification is the most common in the food security literature [16,44], possibly because normal distribution accommodates household heterogeneity more than logistic distribution. Hence, we primarily use the ordered probit model. However, the results of the ordered logit model and ORFs are presented for robustness.

Under the probit or logistic specification of F, let $\alpha_0 = -\infty$. For 2 thresholds of utility $0 < \alpha_1 < \alpha_2$, all probabilities will be nonnegative. The marginal effects of the kth predictor on the probability of food security can be computed as follows:

$$\frac{\partial Prob(FS_i = v|X_i)}{\partial X_{ki}} = \left\{F'\left(\alpha_{j-1} - X_i'\beta\right) - F'\left(\alpha_j - X_i'\beta\right)\right\}\beta_k \qquad (10)$$

To relax the parametric assumption, we included ORFs in our analysis, which is a more flexible, tree-based, machine learning model for learning the association directly from the data, hence depending less on the previous research. We used 70% of the data as the training sample and the remaining 30% as the test sample. As a part of the data preprocessing, all predictors were standardized, and highly correlated ones were omitted. Moreover, we oversampled underrepresented classes to address the class imbalance problem [45]. A typical random forest algorithm involves the following steps:

(1) Given the food security types FS and a vector of predictors X, randomly sample from the training dataset with replacement.
(2) Grow a decision tree for each drawn sample until no further splits are possible.
(3) Select the split among a randomly selected subset of predictors that generates the best prediction.
(4) Repeat until a large number of trees are grown. We used 10,000 trees.
(5) Report the overall pattern by majority voting among classes.

These steps are performed 10 times in the training sample, fine-tuning parameters each time for better accuracy. The training is complete when a further improvement in predictions is below 0.1^5. The trained model is tested on the held-out 30% sample. We generate the correlation of predicted values with predictors to obtain their associations in a data-driven manner.

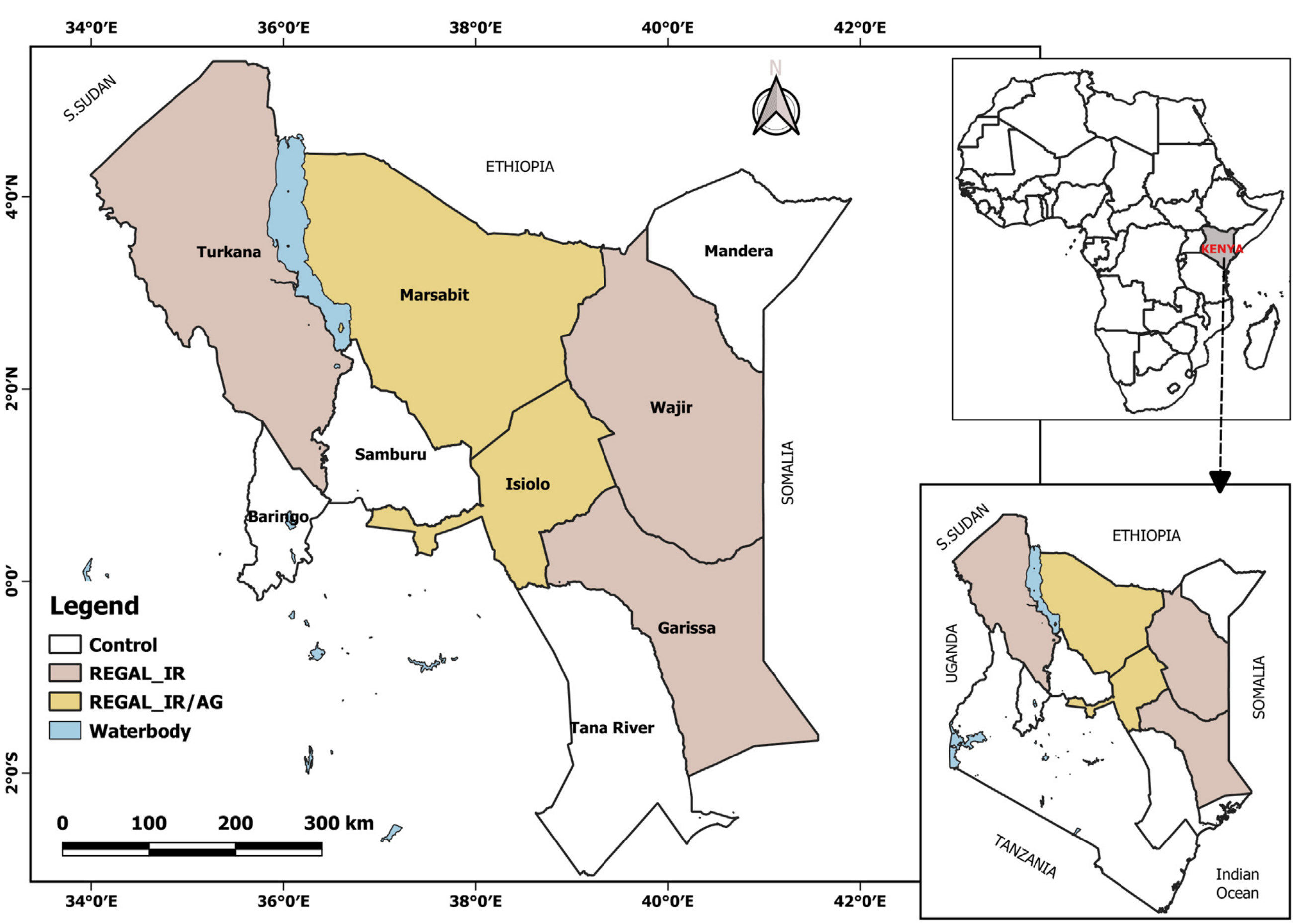

FIGURE 1. Map of Kenya indicating the study area. AG, Accelerated Growth; IR, Improving Resilience; REGAL, Resilience and Economic Growth in Arid Lands.

The ORF follows the random forest algorithm by growing a large number of decision trees by random subsampling and random choice of predictors for a robust prediction. The main difference is that it transforms the ordered variable into multiple overlapping binary variables, and the estimated cumulative probabilities are differenced to find the probabilities of each category. The cumulative probabilities over all categories sum up to 1. For a technical discussion, refer the study by Lechner and Okasa [46].

Data

We use deidentified data from the Feed the Future FEEDBACK Zone of Influence (ZOI) Interim Survey 2015 in Northern Kenya. The de-identified data and data description are publicly available from USAID [47,48]. The survey randomly selected 2,145 households from 44 rural and urban population clusters in 9 counties of Northern Kenya. Figure 1 shows the location of the 9 counties: Garissa, Isiolo, Marsabit, Tana River, Wajir, Baringo, Mandera, Samburu, and Turkana. Notably, a part of the sample was subject to the Resilience and Economic Growth in Arid Lands (REGAL) program implemented by the US Department of State's Feed the Future initiative in 2012–2017. As shown in Figure 1 Marsabit and Isiolo were under REGAL Improving Resilience (IR) and Accelerated Growth (AG) programs, whereas Turkana, Wajir, and Garissa were under the REGAL-IR program only. The remaining 4 counties were not part of these 2 programs. The IR program aims at capacity building and coping with recurring drought, and the AG program aims at enhancing livestock management for economic growth in pastoral communities. Details of these programs are available in respective reports from Feed the Future [49,50].

The Feed the Future initiative used 5 indicators, namely prevalence of poverty, daily per capita expenditures, stunting, underweight, and prevalence of exclusive breastfeeding to calculate the sample size for each population cluster. Sample sizes were further adjusted for a standard nonresponse rate and weighted by population so that the results accurately reflected the proportions of the sample elements within the overall sample frame of the population in the ZOI. A total sample size of 2,100 households was calculated to be adequate to provide estimates of the population-based indicators with an acceptable level of statistical accuracy. During the field survey, 1,837 households were available for interviews, whereas information on some key variables was missing for some households. After downloading the data from Data.gov and removing the incomplete responses, the final sample size included 1,542 households. We used a Heckman [51] 2-step sample selection procedure to address the possible sample selection bias. The results of the first step of the Heckman selection process are presented in Supplemental Table 1.

As discussed in the literature section, the survey included the 6-item HFSSM questionnaire along with questions about households'

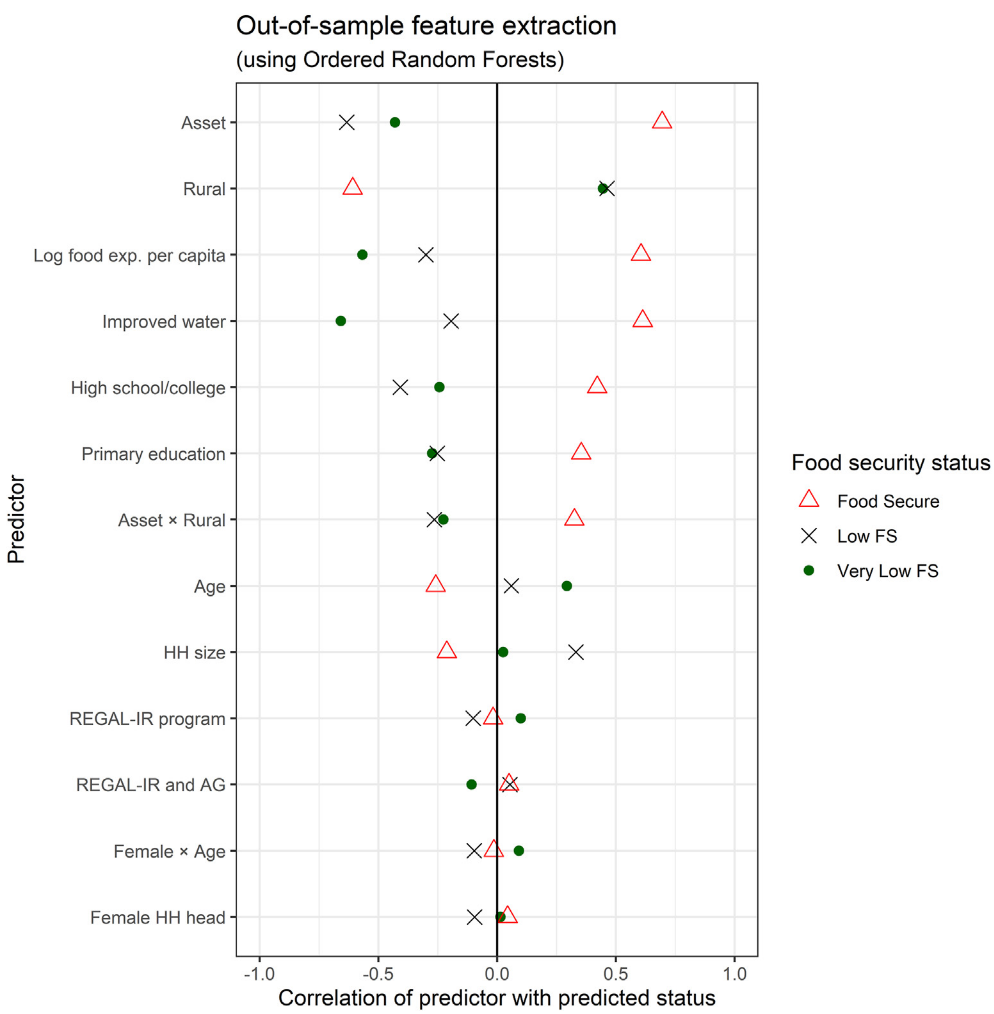

FIGURE 2. Predictors of food security extracted by the ordered random forest model. Predictors are placed on the vertical axis by the order of their correlation with predicted food security status. Greater correlations imply more important feature of the respective food security status. The model included all variables reported in the summary statistics. See Table 2 for variable description. AG, Accelerated Growth; exp, expenditure; HH, household; IR, Improving Resilience; REGAL, Resilience and Economic Growth in Arid Lands.

demographic, economic, and social standings. The questions in the 6-item module and response options are presented in Table 1. Response options "yes," "often," and "sometimes" are taken as affirmative responses, and "rarely" and "no" are taken as negative responses. In a binary setting, affirmative responses are assigned a value of 1 and negative responses 0. The raw score ranged between 0 and 6 on the summation of the numerical values of the responses. Following Abadi et al. [52], the raw scores were divided into 3 groups using 2 equidistant thresholds: 2 and 4. Thus, 3 categories of food security are formed for the estimation purpose, and these 3 food security levels are converted into an ordered variable representing the food security status of the households, where a value of 0 indicates that the household has very low food security, 1 indicates that the household has low food security, and 2 indicates that the household has food security.

Results

Table 2 presents the description and summary statistics of the ordered dependent variables and independent variables, which potentially explain food security. Supplemental Table 2 presents the summary of the response variable by county. Turkana was the least food secure county with 54.3% of the sampled households having low food security and 16.4% very low food security. This observation is similar to the finding of the study by Forsen et al. [53]. Turkana was followed by Mandera where 51.6% of the sampled households had low food security and 4.6% had very low food security. Of the 9 sampled counties, Garissa was relatively the most food secure county.

Results from χ^2 tests and Pearson correlation coefficients

First, we used the χ^2 test to investigate the association between food security status and categorical socioeconomic variables in the data. In addition, binary variables indicating REGAL-IR and REGAL-IR plus AG program areas were included because participation in such programs may enhance household food security. Supplemental Table 3 summarizes the difference in variable means across food security status and detailed results of the χ^2 tests. The results indicate that there is a statistically significant association between household food security status and education, ownership of livestock, durable assets, residing in rural areas, participation in a food security program, and access to improved water. Supplemental Table 3 suggests rejecting the null hypothesis that these variables are independent of the household's food security status. For instance, the food security status of households living in urban areas and those living in rural areas are statistically

TABLE 1
The US 6-item HFSSM questions and response options

Question	Response
1. In the past 30 days were there instances when the household went a whole day and night completely without food due to lack of resources to get food?	Yes/no
2. How often did this happen in the past 30 days?	Rarely/sometimes/often
3. In the past 30 days, did you or any household member go to sleep at night hungry because there was not enough food?	Yes/no
4. How often did this happen in the past 30 days?	Rarely/sometimes/often
5. In the past 30 days, did you or any household member go a whole day and night without eating anything at all because there was not enough food?	Yes/no
6. How often did this happen in the past 30 days?	Rarely/sometimes

Adapted from Feed the Future FEEDBACK (2015). See the Data subsection for details.
HFSSM, Household Food Security Survey Module.

TABLE 2
Description of the variables used in the analysis

Variables	Description and measurement	Mean	SD
Dependent variable			
Food security	Ordered variable: = 0 if HH has very low food security, = 1 if low food security, = 2 if HH is food secure		
	Share of very low food secure HH	0.046	0.209
	Share of low food secure HH	0.345	0.476
	Share of food secure HH	0.608	0.488
Independent variables			
Food expenditure	Daily per capita food expenditure in Kenyan Shillings	38.501	33.711
Age (y)	Age of the household head in years	45.408	16.397
HH size	Number of HH members in the HH (not including the HH head)	4.660	2.245
Female sex	1 if HH head is a woman, 0 otherwise	0.290	0.454
Education	Factor variable on HH head's education level: = 0 if below primary; = 1 if primary; = 2 if secondary/college		
	Share of below primary education	0.699	0.459
	Share of primary education	0.235	0.424
	Share of secondary/college	0.066	0.248
Assets	1 if HH own assets, 0 otherwise	0.145	0.352
FS program	Factor variable on food security program area = 0 if HH is outside program area; = 1 if HH is in REGAL-IR; = 2 if HH is in both REGAL-IR and REGAL-AG		
	Share of HHs outside the program area	0.351	0.477
	Share of HHs in REGAL-IR	0.324	0.468
	Share of HHs in both REGAL-IR and AG	0.325	0.468
Rural	1 if HH live in a rural area, 0 otherwise	0.741	0.438
Livestock	Number of livestock owned	3.219	7.199

Authors' calculation from USAID Feed the Future 2015 data.
AG, Accelerated Growth; HH, household; IR, Improving Resilience; REGAL, Resilience and Economic Growth in Arid Lands.

different. In line with previous studies, household size seems to have a significant association with food security status.

Before applying a regression or machine learning model, it is important to check that the selected predictors do not have strong associations among them. We used the Pearson correlation coefficient as a measure of association between the explanatory variables. The Pearson correlation coefficient for each pair of predictors helps determine the presence and strengths of the linear relationship between variables [54]. The correlation matrix is presented in Supplemental Figure 1. None of the pairs of predictors showed a high positive or negative correlation. The maximum (absolute) correlation coefficient was −0.37, found between assets and rural households.

Following the observations from the literature, χ^2 tests, and correlation coefficients, we proceeded with per capita food expenditure, age, sex, education level, asset ownership, household size, food security program participation, and improved water access for the ordered probit analysis.

Probit model results

Table 3 presents the ordered probit estimates and their marginal effects on all 3 food security types. The inverse Mill ratio showed a negative significant coefficient—confirming the validity of the Heckman selection process. Not surprisingly, the probability of food security increases along with an increase in household daily food expenditure. An increase in per capita food expenditure by 1% was associated with being 22.1% more likely to be food secure in Northern Kenya, holding other predictors at their means. On the contrary, an increase in household daily food expenditure by 1% was related to the probability of the household having low food security and very low food security by 18.8% and 3.3%, respectively. This is intuitive because the sum of all 3 marginal effects for each predictor is zero. These findings support those of Melgar-Quinonez et al. [19] who observe that food-secure households have higher daily per capita food expenditure compared with their counterparts in Bolivia, the Philippines, and Burkina Faso.

The probability of a household being food secure increases at higher levels of education. A household head with primary education was associated with an increase in the probability of food security by 24.7% as opposed to a household with its head lacking primary education. Moreover, a household head with a high school or college education related to a 27% increase in the probability of food security. On the flip side, having primary

TABLE 3
Ordered probit regression coefficients and marginal effects

Variables	(1) Coefficient	(2) Marginal effects	(3)	(4)
		Very low food security	Low food security	Food secure
Log per capita food expenditure	0.577***	−0.0330***	−0.188***	0.221***
	(0.0685)	(0.00513)	(0.0235)	(0.0263)
Age of HH head	−0.00144	8.22×10^{-5}	0.000468	−0.000550
	(0.00273)	(0.000157)	(0.000891)	(0.00105)
HH head is female	0.270	−0.0142	−0.0874	0.102
	(0.219)	(0.0106)	(0.0702)	(0.0807)
Female × Age of HH head	−0.00455	0.000260	0.00148	−0.00174
	(0.00417)	(0.000239)	(0.00136)	(0.00160)
Primary education	0.709***	−0.0288***	−0.219***	0.247***
	(0.158)	(0.00553)	(0.0445)	(0.0484)
High school/college	0.863***	−0.0244***	−0.246***	0.270***
	(0.237)	(0.00415)	(0.0513)	(0.0536)
Assets	1.589***	−0.0402***	−0.387***	0.427***
	(0.313)	(0.00618)	(0.0424)	(0.0454)
Rural HH	−0.186**	0.00971**	0.0604**	−0.0701**
	(0.0938)	(0.00469)	(0.0302)	(0.0347)
Assets × RuralRural HH	−0.0324	0.00191	0.0105	−0.0125
	(0.270)	(0.0163)	(0.0879)	(0.104)
Improved water	0.665***	−0.0428***	−0.210***	0.253***
	(0.143)	(0.0113)	(0.0430)	(0.0529)
REGAL-IR program	0.195**	−0.0105**	−0.0635**	0.0741**
	(0.0843)	(0.00427)	(0.0274)	(0.0315)
REGAL-IR and AG	0.172*	−0.00935**	−0.0561*	0.0654**
	(0.0882)	(0.00448)	(0.0288)	(0.0331)
HH size	0.00784	−0.000449	−0.00256	0.00300
	(0.0172)	(0.000989)	(0.00559)	(0.00658)
Inverse Mill ratio	−1.519***	0.0869***	0.495***	−0.582***
	(0.472)	(0.0278)	(0.156)	(0.181)
Constant 1	0.0643	—	—	—
	(0.292)	—	—	—
Constant 2	1.750***	—	—	—
	(0.298)	—	—	—
Observations (HHs)	1542	1542	1542	1542

Note: Robust standard errors in the parentheses. Pseudo-$R^2 = 0.129$; log pseudo likelihood= −1104.710; $P > \chi^2 = 0.0001$. Asterisks *, **, and *** stand for significance levels at 10%, 5% and 1%, respectively. See Table 2 for variable descriptions.
AG, Accelerated Growth; HH, household; IR, Improving Resilience; REGAL, Resilience and Economic Growth in Arid Lands.

education was associated with 2.8% and 21.9% less probability of very low food security and low food security, respectively. For high school or college education, the drop was 2.4% and 24%, respectively. The positive relationship can be attributed to greater employment opportunities and nutritional knowledge. These results corroborate those of Magaña-Lemus et al. [16], Lee and Frongillo [55], Gebre [30], and Bashir et al. [35], who found that the education of household head increases the likelihood of a household being food secure compared with household headed by a person with no formal education. Education contributes to increased work productivity, skills, income diversification, and adoption of better technologies by farmers and encourages parents to invest in their children [30]. Households with durable assets were 42.7% more likely to be food secure in our sample, 21.9% less likely to have low food security, and 2.8% less likely to have very low food security. Assets are a form of wealth, and households can liquidate them at times of difficulty to buy food. These findings match those by Abdullah et al. [28] and Gebre [30], who found households with durable assets to be more food secure compared with households with no assets.

The location of the household matters too. Households living in rural areas were 7% less likely to be food secure in the sample, 6% more likely to have low food security, and ~0.9% more likely to have very low food security, compared with the households living in urban areas. These findings are consistent with those of Magaña-Lemus et al. [16] who found households living in rural areas may lack food security more than those in urban areas.

Access to improved water resources was related to an increase in the probability of food security by 25.3% and to a decrease in the probability of a household having very low and low food security by −4.2% and −21%, respectively. This finding supports the results of Misra [39] who found that depletion of freshwater reduces agricultural production, hence reducing food production. Moreover, food security and distance to the nearest water source and inadequate rainfall are closely related [36,56,57].

Finally, the presence of both REGAL-IR and REGAL-IR plus AG programs showed positive significant associations with household food security by 7.4% and 6.5%, respectively. This seemed counterintuitive at first because the effect of 1 program (IR) should have been smaller than 2 concurrent programs (IR and AG). We further elaborate on this in the following subsections.

As discussed in the Methods and Data section, the coefficient estimates and marginal effects of the ordered logit model are presented in Supplemental Table 4. Assuming a logistic distribution for the unobserved household characteristics generated similar results. The signs and statistical significance of all estimates were consistent with the probit results.

TABLE 4
Regression coefficients and marginal effects for rural households

Variables	(1) Coefficient	(2) Marginal effects	(3)	(4)
		Very low food security	Low food security	Food secure
Log per capita food expenditure	0.561***	−0.0474***	−0.175***	0.223***
	(0.0738)	(0.00733)	(0.0248)	(0.0293)
Age of HH head	−0.00111	9.38×10^{-5}	0.000347	−0.000441
	(0.00294)	(0.000250)	(0.000918)	(0.00117)
HH head is female	0.564**	−0.0406***	−0.177**	0.218**
	(0.240)	(0.0154)	(0.0738)	(0.0883)
Female × Age of HH head	−0.00931**	0.000787**	0.00291**	−0.00370**
	(0.00453)	(0.000389)	(0.00142)	(0.00180)
Primary education	0.833***	−0.0446***	−0.257***	0.301***
	(0.178)	(0.00731)	(0.0500)	(0.0546)
High school/college	0.877***	−0.0368***	−0.263***	0.300***
	(0.289)	(0.00629)	(0.0708)	(0.0746)
Assets	1.800***	−0.0506***	−0.422***	0.472***
	(0.355)	(0.00688)	(0.0363)	(0.0377)
Improved water	0.779***	−0.0659***	−0.235***	0.301***
	(0.166)	(0.0157)	(0.0475)	(0.0608)
REGAL-IR program	0.242***	−0.0192***	−0.0762**	0.0954***
	(0.0929)	(0.00683)	(0.0298)	(0.0362)
REGAL-IR and AG	0.258***	−0.0201***	−0.0815**	0.102***
	(0.0986)	(0.00704)	(0.0317)	(0.0383)
HH size	−0.00326	0.000276	0.00102	−0.00130
	(0.0192)	(0.00162)	(0.00600)	(0.00762)
Inverse Mill ratio	−1.983***	0.168***	0.620***	−0.787***
	(0.577)	(0.0494)	(0.184)	(0.229)
Constant 1	0.183	—	—	—
	(0.292)	—	—	—
Constant 2	1.846***	—	—	—
	(0.299)	—	—	—
Observations (HHs)	1169	1169	1169	1169

Note: Robust standard errors in the parentheses. Pseudo-$R^2 = 0.090$; log pseudo likelihood= −920.354; $P > \chi^2 = 0.0001$. Asterisks *, **, and *** stand for significance levels at 10%, 5% and 1%, respectively. See Table 2 for variable descriptions.
AG, Accelerated Growth; HH, household; IR, Improving Resilience; REGAL, Resilience and Economic Growth in Arid Lands.

Machine learning results

Figure 2 presents the association between predictors and food security status generated by the ORF. These associations were pessimistically generated using the 30% held-out sample. The overall accuracy rate was 84.92%. However, the main objective of this part was to extract features of food security rather than predict food security. The correlation coefficients on the horizontal axis show both the direction and normalized magnitude of association with food security. Predictors are placed on the vertical axis by the order of their correlation with the predicted food security status. Asset ownership, daily food expenditure per capita, access to improved water, and education variables were found to have a positive association with food security; whereas households located in rural areas, having older household heads, and bigger household sizes showed a negative association with food security. Low food secure households and very low food secure households exhibited almost similar patterns, yet an opposite pattern of food secure households. Moreover, the interaction of asset and location exhibited a positive association with food security, indicating rural households with assets are more likely to have food security. To summarize, without imposing distributional assumptions on the unobserved household-specific factors, these results imply that the sociodemographic characteristics of food secure and not food secure households are strikingly different, especially for asset ownership, location, education, age, food expenditure, access to water, and household size. These findings were similar to the results from the probit model.

A closer look at the importance of location in food security

The abovementioned results suggest that households in rural Northern Kenya are more likely to lack food security. To learn whether the pattern of food security varies with the level of urbanization, we repeated the analysis separately for rural and urban households. Results are placed in Tables 4 and 5, respectively. In both cases, food expenditure and asset ownership were significant. Households with primary education were likely to be food secure in rural areas, but not in urban areas. Urban households made a difference when household heads were educated up to high school or college.

Other predictors such as female household heads, access to improved water, and food security programs in urban areas were not significant, whereas they were significant in rural areas (Tables 4 and 5). In addition, food security programs seemed more significant for rural samples; households in REGAL-IR program were 9.5% more likely to be food secure, whereas households in REGAL-IR and AG programs were 10.2% more likely to be food secure compared to households in the nonprogram areas. Thus, REGAL-IR and AG program showed a stronger association with food security than the IR program alone. The aggregation of the rural and urban samples might

TABLE 5

Regression coefficients and marginal effects for urban households

Variables	(1) Coefficient	(2) Marginal effects	(3)	(4)
		Very low food security	Low food security	Food secure
Log per capita food expenditure	0.803***	−0.00426	−0.207***	0.211***
	(0.220)	(0.00309)	(0.0594)	(0.0598)
Age of HH head	−0.000708	3.75×10^{-6}	0.000183	−0.000186
	(0.00771)	(4.05×10^{-5})	(0.00199)	(0.00203)
HH head is female	−0.584	0.00420	0.159	−0.163
	(0.565)	(0.00652)	(0.159)	(0.165)
Female × Age of HH head	0.0106	-5.64×10^{-5}	−0.00274	0.00280
	(0.0106)	(7.13×10^{-5})	(0.00273)	(0.00278)
Primary education	0.446	−0.00222	−0.110	0.113
	(0.407)	(0.00238)	(0.0972)	(0.0989)
High school/college	0.650	−0.00189	−0.131*	0.133*
	(0.506)	(0.00159)	(0.0756)	(0.0762)
Assets	1.158**	−0.00600	−0.260**	0.266**
	(0.587)	(0.00503)	(0.115)	(0.118)
Improved water	0.535	−0.00513	−0.157	0.162
	(0.427)	(0.00680)	(0.139)	(0.145)
REGAL-IR program	−0.00816	4.35×10^{-5}	0.00211	−0.00215
	(0.221)	(0.00118)	(0.0571)	(0.0583)
REGAL-IR and AG	−0.0632	0.000341	0.0164	−0.0167
	(0.234)	(0.00136)	(0.0608)	(0.0622)
HH size	0.0558	−0.000296	−0.0144	0.0147
	(0.0412)	(0.000315)	(0.0107)	(0.0109)
Inverse Mill ratio	−0.700	0.00371	0.181	−0.184
	(1.159)	(0.00622)	(0.301)	(0.306)
Constant 1	0.735	—	—	—
	(0.917)	—	—	—
Constant 2	2.763***	—	—	—
	(0.942)	—	—	—
Observations (HHs)	373	373	373	373

Note: Robust standard errors in the parentheses. Pseudo-$R^2 = 0.210$; log pseudo likelihood= −174.909; $P > \chi^2 = 0.0001$. Asterisks *, **, and *** stand for significance levels at 10%, 5% and 1%, respectively. See Table 2 for variable descriptions.
AG, Accelerated Growth; HH, household; IR, Improving Resilience; REGAL, Resilience and Economic Growth in Arid Lands.

have generated the counterintuitive estimates discussed earlier (Table 3).

Unlike the aforementioned combined rural–urban model (Table 3), having a female household head was positively associated with food security in rural households. The result is consistent with some other studies that observed rural African women improving their food security by taking charge of the household because their men are abusive or constantly away [37, 58]. However, the association decreases as female household heads become older. Finally, access to improved water is one of the key indicators of food security, perhaps because of the lack of universal access to clean water in rural areas [59].

The role of owning and rearing livestock in rural areas

The aforementioned results suggest that asset ownership is one of the major predictors of food security, for both urban and rural households. However, a large part of assets in rural households consists of livestock. Livestock is an important source of livelihood for rural households in Northern Kenya because pastoralism and agropastoralism are their main livelihood; whereas it is not so important for urban households because most of the urban households do not keep livestock. We included the livestock count variable and replicated the probit model for rural households to see how the number of livestock affects the food security status of the households. The results are presented in Table 6.

Most predictors that were statistically significant for the rural model before remained significant. Livestock turns out to be an important predictor of food security in rural areas. An increase in livestock by 1 animal was associated with an increase in the chance of a household being food secure by 0.8%. These results support those of Godber and Wall [60] who found that livestock is a major contributor to sustainable food security in marginalized areas. Jodlowski et al. [61] found that ownership of livestock by smallholders improves household food dietary diversity because of direct consumption of animal products and through an increase in consumption expenditure. Similarly, Mahmood et al. [62] found that an increase in meat and milk-producing animals increases the food security of rural households in Pakistan. Thus, livestock contributes directly to nutrition security and indirectly to food security through the sale of livestock and milk, which is used to buy staple foods [63].

Discussion

Our findings have several policy implications. First, results show that the education of the household head plays an important role in the food security of the rural community in Northern

TABLE 6

Regression coefficients and marginal effects for rural households with the livestock count variable

Variables	(1) Coefficient	(2) Marginal effects	(3)	(4)
		Very low food security	Low food security	Food secure
Log per capita food expenditure	0.686***	−0.0401***	−0.228***	0.268***
	(0.0825)	(0.00718)	(0.0297)	(0.0321)
Age of HH head	−0.000675	3.94×10^{-5}	0.000224	−0.000264
	(0.00332)	(0.000195)	(0.00110)	(0.00130)
HH head is female	0.533**	−0.0262**	−0.174**	0.201**
	(0.269)	(0.0120)	(0.0851)	(0.0961)
Female × Age of HH head	−0.00735	0.000429	0.00244	−0.00287
	(0.00520)	(0.000309)	(0.00173)	(0.00203)
Primary education	1.059***	−0.0350***	−0.316***	0.351***
	(0.214)	(0.00650)	(0.0514)	(0.0534)
High school/college	0.863***	−0.0240***	−0.257***	0.281***
	(0.323)	(0.00521)	(0.0743)	(0.0767)
Assets	2.093***	−0.0365***	−0.434***	0.470***
	(0.410)	(0.00679)	(0.0296)	(0.0305)
Improved water	0.925***	−0.0571***	−0.291***	0.348***
	(0.182)	(0.0141)	(0.0530)	(0.0633)
REGAL-IR program	0.280**	−0.0147***	−0.0928**	0.108***
	(0.110)	(0.00543)	(0.0366)	(0.0413)
REGAL-IR and AG	0.141	−0.00794	−0.0469	0.0548
	(0.109)	(0.00584)	(0.0364)	(0.0420)
HH size	0.0187	−0.00109	−0.00623	0.00732
	(0.0240)	(0.00144)	(0.00797)	(0.00939)
Number of livestock	0.0216***	−0.00126***	−0.00717***	0.00843***
	(0.00599)	(0.000389)	(0.00202)	(0.00234)
Inverse Mill ratio	−2.528***	0.148***	0.841***	−0.988***
	(0.628)	(0.0392)	(0.215)	(0.245)
Constant 1	0.587*	—	—	—
	(0.328)	—	—	—
Constant 2	2.346***	—	—	—
	(0.335)	—	—	—
Observations (HHs)	883	883	883	883

Note: Robust standard errors in the parentheses. Pseudo-$R^2 = 0.113$; log pseudo likelihood= −647.768; $P > \chi^2 = 0.0001$. Asterisks *, **, and *** stand for significance levels at 10%, 5% and 1%, respectively. See Table 2 for variable descriptions.

AG, Accelerated Growth; HH, household; IR, Improving Resilience; REGAL, Resilience and Economic Growth in Arid Lands.

Kenya. Even primary education creates a noticeable difference in rural food security, whereas high school or college education is a more prominent feature of urban food security. This is critical because most of the household heads in rural Northern Kenya are without formal education. Education may contribute to generating off-farm income and investing in children, thus improving food security. Therefore, special programs and long-term policies are needed for schooling the children.

Second, we found that access to improved water is important for the food security of rural households in Northern Kenya. Safe supplied water is not available in the rural parts of Northern Kenya, while the natural sources of water get depleted during the dry season, especially in the events of droughts. Therefore, the Kenyan government and the global development community need to invest in the provision of safe water supply in the rural parts of Northern Kenya.

Third, although field observation suggested that livestock rearing is the main source of income for rural households in the arid and semi-arid lands of Northern Kenya, our results confirmed that it is highly important for their food security. With almost no rain during the dry season, not only do livestock animals experience shortage of drinking water but also grazing lands become bare and the pastoral households move their animals to far places in search of vegetation and water for livestock. A considerable number of animals die during frequent droughts the region experiences, thus depleting the availability of food to the households. This implies that the Kenyan government and the global development community need to invest in alternative sources of animal feed and water for the sustainable food security of the rural population.

Finally, rural food security has a multidimensional structure, whereas urban food security is mainly explained by higher education, per capita spending on food, and household assets. In addition, it is important to notice that the REGAL programs show significant positive association with food security in rural Northern Kenya, especially when both IR and AG programs are combined. So, an expansion of such programs in rural areas may contribute to food security.

This article presents the results of an empirical analysis of the key factors influencing the food security of the households of Northern Kenya. However, in the face of a growing population and changing climate, improvements in a few factors may not be enough to guarantee the food security of the people in Northern Kenya in the coming decades. The issues of food security, especially in rural areas, are multidimensional, hence should be tackled from an integrated systemic point of view as food access, availability, utilization, and stability.

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Data Availability

The data described in the article, code book, and analytic code will be made publicly and freely available without restriction at https://github.com/Badruddoza/Northern-Kenya-Project.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cdnut.2022.100005.

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