Food Security of Farm Households in Impoverished West African Countries: A Case for Machine Learning?

Jaehyun Ahn

979-458-0193

hyun81219@tamu.edu

Department of Agricultural Leadership, Education & Communications

Texas A&M University

600 John Kimbrough Blvd

2116 TAMU

College Station, TX 77843

Alexis Zickafoose

937-509-1768

alexis.zickafoose@ag.tamu.edu

Department of Agricultural Leadership, Education & Communications

Texas A&M University

600 John Kimbrough Blvd

2116 TAMU

College Station, TX 77843

Mathew Baker

979-845-6944

Mathew.Baker@ag.tamu.edu

Department of Agricultural Leadership, Education & Communications

Texas A&M University

600 John Kimbrough Blvd

2116 TAMU

College Station, TX 77843

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In Africa, Liberia is the eighth and Senegal is the 29th poorest country (World Bank, n.d.). Both countries are below the mean GNI of 2.227K ($US). The Food and Agriculture Organization (2007) defines food security as a state of well-being when people enjoy sufficient, preferable, nutritious, and safe food to maintain healthy and productive lives. Gibson (2012) was concerned with how societies meet these standards. Communities in both the U.S. and abroad struggle to meet these standards. Thirty-three million smallholder farms supply 70% of the food in Africa, those households suffer the most from persistent poverty and food insecurity (Doss et al., 2018; IFAD, 2017).

This research made use of the FAO's Food Security Framework (RTI, 2014) to classify households into an ordinal continuum (i.e., when collecting on-farm, household-level data. This classification was based upon food availability, access, utilization, and stability. As these were subsistence farmers, household composition, farm, and non-farm income and activities were examined as drivers of food insecurity (Landaverde et al., 2021; Samim, 2021; Ahn, 2020). Therefore, this study aligns with the AAAE National Research Agenda of *Addressing Complex Problems* (Roberts et al., 2016). This priority area seeks innovative strategies to address food insecurity by integrating behavioral approaches into new solutions. Machine learning techniques are used to identify important factors that contribute to food insecurity in West Africa.

Methodology

A household security questionnaire was conducted in selected regions of Liberia and Senegal September 2012 to March 2013 by Texas A&M University. Severely food insecure households experienced a food shortage for three months or more with scarce availability and access; moderately food insecure households experienced a food shortage for three months with difficulty procuring quality nutritious food; mildly food secure households had food shortages of two months or fewer. In Liberia, 323 households were surveyed and categorized (129 severe, 112 moderate, and 82 mild). In Senegal, 510 households were surveyed and categorized (167 severe, 230 moderate, 113 mild). A direct relationship was hypothesized between farm costs, returns, off-farm income, and food security. Income calculations included crops, livestock, off-farm, and credit. Climate, community support, market, head of household gender, household dependents, technology, agricultural information, consumption of animals, location, presence of land conflict, and farm labor-force were identified as food insecurity predictors.

Machine learning was used to prioritize the factors leading to food insecurity and confirm observed field data. To this end, Exhaustive Chi-squared Automatic Interaction Detectors (CHAID) was used due to the ordinal nature of the data for each country. Categorizing predictor choice by relevance and importance to the target and tolerance of skewed data were reasons to use this method (Song & Ying, 2015). V-fold cross-validation helped evaluate the accuracy of predicted classification since CHAID algorithm entails conceivable overfitting risk from single tree construction. In addition to the pooled and country-level findings in Liberia and Senegal, the researchers were interested in comparing the CHAID results to similar household-level studies conducted where ordered probit techniques were used to classify households in Afghanistan (Samim, 2021), and a qualitative approach used in El Salvador (Landaverde et al., 2021) which are discussed in the Implications section of this abstract.

Results

The most important predictor identified by CHAID for both Liberia and Senegal was community support. For Liberian households which were classified to be severely food insecure, their predictors were local markets, growing upland rice, lack of agricultural information, off farm income, land conflict, and county of residence respectively. Moderately food insecure households in Liberia categorized selling channel, head of household's gender, and farm labor as important predictors. Machine learning accurately classified 104 severely food-insecure, 61 moderately food-insecure, and 73 mildly food-secure households out of 323 households. A risk estimate of v-fold cross-validation of 31.6% and a 26% misclassification rate of the training data despite almost the same 0.02 standard error was observed. In Senegal, the predictors for the majority moderately food insecure were consuming animals, credit, crop income, off-farm income, and female head of household respectively. Those severely food insecure had similar predictors except credit and off-farm income were not selected as important predictors. Machine learning accurately classified 127 severely food insecure, 202 moderately food insecure, and 77 mildly food secure households out of 510 households. Senegal had a 20% misclassification rate for training data and a 25% v-fold cross-validation risk.

Conclusions

Predictors classified more severely food-insecure households in Liberia and moderately food-insecure households in Senegal. Seeking possibilities for communities to support each other financially could increase both male and female-led households' farm capacities and alleviate food insecurity. For Liberia, access to out-of-village selling channels, resilient crop varieties, more agricultural information and off-farm income, and less land conflict could promote food security in the region. In Senegal, to uplift those with both severely and moderately food insecure households, extensionists should focus on increasing animal consumption, providing access to credit, increasing crop production, and encourage off-farm income while targeting female-led households. Despite the misclassification rates, CHAID can provide guidance for designing country-specific programs to increase food security.

In this study near the most food-insecure months, extensionists should assist farmers by providing more agricultural information, knowledge, and techniques to each village, and introducing additional off-farm activities closely related to agriculture. Tailored education and extension programs may be more attuned to the needs of the people they aim to help. National organizations could use the same methods to retroactively learn and identify priorities in their own communities.

Implications

Our results were like results reported in Afghanistan (Samim, 2021) and El Salvador (Landaverde et al., 2021). Collecting and measuring fundamental data are key to better understanding the dynamics at play in households of marginalized farmers in the poorest regions of the world. With this said, there seems to be a trend in poorer countries where household dynamics are being included in these analyses. This is a very good trend, but it is time consuming and expensive. Further research is still needed. Decision tree classifiers are underutilized in the context of food security, and more evidence from more cases over extended periods is needed. A timely, systematic, and just study is necessary for national and international rural communities whose farming and social environment is changing rapidly.

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