Analysis of households' vulnerability to food insecurity in the face of climate variability: Evidence from North Shewa Zone, Amhara Region, Ethiopia

debebe cheber bezu (debebec2012@gmail.com)
Jimma University College of Agriculture and Veterinary Medicine

Fekadu Beyene
Haramaya University College of Agricultural and Environmental Sciences

Jema Haji
Haramaya University College of Agricultural and Environmental Sciences

Tesfaye Lemma
Haramaya University College of Agricultural and Environmental Sciences

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Analysis of households' vulnerability to food insecurity in the face of climate variability: Evidence from North Shewa Zone, Amhara Region, Ethiopia

Debebe Cheber[1,*], Fekadu Beyene[2], Jema Haji[3], Tesfaye Lemma[2]

[1] Department of Rural Development and Agricultural Extension, Jimma University, Ethiopia

[2] School of Rural Development and Agricultural Innovation, Haramaya University, Ethiopia

[3] School of Agricultural Economics and Agribusiness Management, Haramaya University, Ethiopia

*Corresponding author: E-mail: debebec2012@gmail.com. Tel: +251-0913-177930.

Abstract

Most studies conducted in Ethiopia have given attention to the study of static food insecurity with no concern on vulnerability to food insecurity. An understanding of vulnerability to food insecurity is critically important to inform the formulation of policies and strategies to enhance food security and reduce vulnerability to food insecurity among households. Thus, this study examined the level of households' vulnerability to food insecurity and its determinants in North Shewa zone of Ethiopia using cross-sectional data collected from 382 sample households. The vulnerability of households to food insecurity was estimated using vulnerability as expected poverty approach. The factors which influenced vulnerability to food insecurity were analyzed using logistic regression model. Accordingly, based on the intensity of their vulnerability, households were grouped as chronic food insecure (43.72%), transient food insecure (12.57%), highly vulnerable-food secure (16.23%), and low vulnerable-food secure (27.49%). Overall, about 75.51% of households were categorized as vulnerable to food insecurity. These included households who were food insecure at the time of the survey (56.28%) and those who were categorized as transient food secure group (16.23%). In addition, logistic regression model results revealed that extension service, early warning information, agricultural technology, and crop diversity were the major factors affecting (negatively) households' vulnerability to food insecurity. On the other hand, sex, rainfall variability and drought have increased the probability of being vulnerable to food insecurity. The findings imply that design and implementation of food insecurity policies and strategies need to focus not only on households that are currently food insecure, but also on those categorized as transient food insecure or households that are more likely to be food insecure in the near future.

Keywords: Household, Vulnerability, Food insecurity, Climate variability, Ethiopia.

1. BACKGROUND OF THE STUDY

A number of scholars argued that global land and sea temperatures are warming under the influence of greenhouse gases (IPCC, 2007). Continuous increment of the gas emissions result in global warming that promote sea level rise, rapid breakup of ice sheets, changes in precipitation over land and other unexpected shocks (IPCC, 2014). Recently, worldwide drought increased in frequency, severity, and duration (Peterson *et al.,* 2013). Extreme weather events like severe storms, floods, droughts and heat waves are becoming more frequent and intense recently (IPCC, 2014). Sushenjit and Emmanuel (2013) argued that climate change could increase the number of extreme temperature and rainfall inconsistencies, and hence climate variability showed an upward trend. Recent estimates indicated that unprecedented climate variability mostly occurs in the tropics and among low-income countries, where the projected climate elements continuously move outside the bounds of historical records (Mora *et al.,* 2013).

African countries are at large hit by food insecurity incidence mainly due to increase in climate variability that led to decreases in crop yields (HLPE, 2012; Badolo and Romuald, 2015) and which suggests that many households are vulnerable to it. The effect is particularly pronounced in the rural households of developing countries such as Ethiopia where the capacity to cope with the adverse effect is low (Demeke *et al.,* 2011; Di Falco *et al.,* 2011). With regard to this, different studies indicate that levels of poverty and vulnerability in Ethiopia remain very high (Dercon and Christiaensen 2011; Dercon *et al.,* 2012; Kumar and Quisumbing, 2012; Fentaw *et al.,* 2013; IFPRI, 2015; FAO, 2016). On average, 32% and 40% of the Ethiopia's population are undernourished and consume less than the recommended daily calories, respectively (IFPRI, 2015). Moreover, the FAO (2016) situation report indicates that more than 10.2 million people needed food assistance in 2016, more than at any other time since 2006.

Furthermore, empirical findings by Dercon and Krishnan (1998), Dercon and Christiaensen (2007) and Capaldo *et al.* (2010) also show that in many developing countries, such as Ethiopia, food security is mostly unstable, fluctuating over time. According to Dercon and Krishnan (2000) and Capaldo *et al.* (2010), access to adequate food for many households varies over time due to households' proneness to shocks and other risks, such as rainfall variability, flood, drought, and their capacity to recover and respond. This implies that the concept of food insecurity is best

thought of as dynamic rather than static in nature (Capaldo *et al.,* 2010). It is no surprise that the dynamic nature of food insecurity persists in rural population of Ethiopia where livelihood is derived mainly from agriculture, which is rainfall dependent and highly erratic. As such, it is important to analyze vulnerability to food insecurity (VFI) and identify households that are currently food insecure and those likely to be food insecure in the near future. A proper approach to this would be to carry out a more disaggregated analysis of VFI rather than merely categorizing households as either food secure or food insecure. This is particularly important if the aim is to design and implement inclusive food security policies and strategies that are intended to serve different groups.

This also implies that food security studies that aim to inform the formulation and implementation of policies and programs to address VFI should be based not just on the assessment of households' current conditions, but also on the expected situation of access to food in the near future (Capaldo *et al.,* 2010). In addition, although the emphasis is on analyses of dynamic nature of food insecurity for better and effective policy action, most of the past studies have focused on vulnerability to poverty, not food insecurity (Chaudhuri, 2003; Scaramozzino, 2006). Most food security strategies and program studies conducted in Ethiopia focus on the evaluation of current food insecurity with respect to who is currently food insecure and why (Bogale and Shimelis 2009; Motbainor *et al.,* 2016; Agidew and Singh 2018; Jaleta *et al.,* 2018). They do not go further and attempt to determine who are likely to be VFI in the near future.

Therefore, the objectives of this study were to examine the level of households' vulnerability to food insecurity and its determinants in North Shewa zone of Ethiopia. Thereafter, implications for effective policy interventions to enhance food security and reduce vulnerability to food insecurity in the study area are drawn.

2. CONCEPT OF HOUSEHOLD VULNERABILITY TO FOOD INSECURITY

Food security has been defined as a situation when all people, at all times, have physical and economic access to sufficient, safe and nutritious food needed to maintain a healthy and active life (FAO, 2009). This definition introduces a stability dimension, which points to the need for understanding both current and future statuses of household food security. Moreover, FAO (2009) has shown that access to sufficient, safe and nutritious food in many countries is unstable. Many

households frequently move in and out of a state of food security, suggesting that the notion of food security is best approached in a dynamic sense. Therefore, a framework for analyzing food security must capture its temporal dynamics. Vulnerability analysis offers a solution to this problem by providing a quantitative estimate of the probability that a given household will lose access to sufficient, safe and nutritious food in the near future (Babatunde *et al.,* 2008).

The main advantages of the vulnerability approach are twofold. First, it is explicitly dynamic and forward-looking as it considers both current outcomes and future incidences of food insecurity. Second, the analysis uses a stochastic framework and can therefore fully consider the uncertainties associated with future food insecurity, such as the role of external shocks and the strategies that households, communities or public institutions can adopt in order to reduce the likelihood of negative outcomes (Scaramozzino, 2006). The notion of vulnerability as a risk of shortfall can be expressed as a probability statement regarding the failure to attain a certain wellbeing threshold in the future (Christiaensen and Boisvert, 2002). The probability of becoming food insecure in the future is determined by the present conditions, risks potentially occurring within a defined period and the capacity to manage the risks. At the household level, the major types of risks include health (illness, disability, injuries), life cycle-related (old age, death), social (inequitable intra-household food distribution), economic (unemployment, harvest failure, price changes) and threats related to the natural environment (Babatunde *et al.,* 2008). These risks cause food insecurity by lowering food production, reducing income, reducing assets holding and reducing food consumption (Lovendal and Knowles, 2005).

3. MEASUREMENT OF HOUSEHOLD VULNERABILITY TO FOOD INSECURITY

Although several empirical methodologies of assessing vulnerability to food insecurity have been proposed in the literature, none of them has evolved into a unanimously accepted approach (Ayalneh, 2012). Three different methodologies are commonly used to assess vulnerability and these include vulnerability as uninsured exposure to risk (VUER), vulnerability as low expected utility (VLEU) and vulnerability as expected poverty (VEP) (Hoddinott and Quisumbing, 2003). All three methods construct a measure of welfare loss attributed to shocks, but differ in that VUER and VLEU measure the ex-ante probability of a household's consumption or utility falling below a given minimum level in the future due to current or past shocks, while VEP measures ex-post

welfare loss due to shocks (Hoddinott and Quisumbing, 2003). Therefore, this study employed the VEP approach to measure the ex-post probability of a household's becoming food insecure in the future.

According to VEP approach, an individual's vulnerability is the prospect of that person becoming poor in the future if currently not poor, or the prospect of him/her continuing to be poor if currently poor (Christiaensen and Subbarao, 2004). Thus, vulnerability is seen as expected poverty, while consumption (income) is used as a proxy for well-being. This method estimates the probability of a given shock or set of shocks moving household consumption below a given minimum level (such as a consumption poverty line), or force the consumption level to stay below the minimum if it is already below the level (Chaudhuri *et al.,* 2002). Even though lengthy panel data are preferred for the estimation of household vulnerability using the VUER and VLEU, the VEP approach can be used to assess vulnerability of households based on cross-section data where there is no panel data, as is often the case in developing countries (Gunther and Harttgen, 2009).

4. CONCEPTUAL FRAMEWORK OF THE STUDY

Different international organizations define vulnerability in various ways. Vulnerability to climate variability and change can be defined in several ways as pre-adaptation and post-adaptation vulnerability, outcome vulnerability and conceptual vulnerability. According to the post-adaptation definition, vulnerability refers to the residual impacts of climate change after adaptations options have been taken into account. That is, "the level of vulnerability is determined by the adverse consequences that remain after the process of adaptation has taken place" (Kelly and Adger, 2000). This approach specifically focuses on the physical dimensions of vulnerability. The pre-adaptation definition of vulnerability has its origin in the literature on food security and famine (Bohle *et al.,* 1994) and vulnerability to natural hazards (Blaikie *et al.,* 1994). According to this approach; limited access to resources, political instability and exposure are the main cause of vulnerability. However, this study adopts the definition of the IPCC Third Assessment Report (IPCC, 2001), which defines vulnerability as a function of three dimensions: sensitivity, exposure and adaptive capacity.

Therefore, the context of this study could be viewed as exposed to food insecurity and climate-related factors, such as drought and flood. Exposure in turn affects sensitivity, i.e., exposure to higher frequencies and intensities of climate risk seriously affect economic and social outcomes such as crop yield and income. Exposure is also related to adaptive capacity. Specifically, higher adaptive capacity either reduces the potential damage from or provides resilience against exposure to higher climate risk.

This conceptual framework for vulnerability also suggests that sensitivity and adaptive capacity are interlinked. That is, given some fixed level of exposure, adaptive capacity influences the level of sensitivity. Lower adaptive capacity results in higher sensitivity and vice versa. Hence, sensitivity and adaptive capacity together with exposure add up to overall vulnerability. The conceptual framework also captures socioeconomic vulnerability, which mainly deals with variations within a society (Adger, 1999), and biophysical vulnerability, which emphasizes the adverse effects of environmental factors on human and natural systems (Füssel and Klein, 2006). Thus, this study employed the integrated approach, which tries to integrate both biophysical and socioeconomic factors in analyzing vulnerability to food insecurity.

5. RESEARCH METHODOLOGY

5.1. Description of the Study Area

The study was carried out in North Shewa zone of Amhara Region, Ethiopia. The zone has twenty two rural districts in which seven districts are located in highland agro-ecology, eleven in midland agro-ecology and the remaining four in lowland agro-ecology. Its capital is Debre Berhan and has 387 rural and 55 urban kebeles. According to the Central Statistical Agency (CSA) (2013) population projection, North Shewa zone has a population size of 2,131,857 persons.

Mixed farming is the dominant livelihood source in the study area. Selling local alcoholic drinks, firewood, charcoal and multipurpose Guassa grass are used to supplement local livelihoods. However, most of the districts in the study area are food insecure, and the problem is worse in the highland and midland agro-ecological zone (North Shewa zone Food Security Coordination and Disaster Prevention Office, 2018). According to information from the zone Food Security Coordination and Disaster Prevention Office, large parts of the study area are beneficiaries of the

Productive Safety Nets Program (PSNP). Climate change and variability related risks such as reduced or variable rainfall, warming temperature, crop and livestock pests and diseases, flooding, drought and soil erosion are the major livelihood challenges to farm households of the study area (Arragaw and Woldeamlak, 2017). Current climate change and variability contributes to reduced agricultural productivity and the future sustainability of the sector in the study area depends on the types of coping and adaptation strategies used by farmers.

The study covered six districts, namely Kewot, Ankober, Menz Keya Gebireal, Asagirt, Tarmaber and Angolelana Tera, of North Shewa zone (Figure 1). The total population of the six districts is 446,445 out of which 234,415 are males and 212,030 are females. Kewot is in the lowland agro-ecological zone, Ankober, Menz Keya Gebireal and Asagirt are in the midland agro-ecological zone and, Tarmaber and Angolelana Tera are in the highland agro-ecological zone. Elevation ranges from 1853 m above mean sea level in Kewot to 2473 m above mean sea level in Angolelana Tera. Some 38.6% of the total area of the six districts is mountainous, 36.6% is rugged and 24.8% is plain lands. Based on the soil classification system, Black cover about 21% of the districts, Red brown cover about 41%, Red cover 21%, Gray cover 11% and others account for some 6%. The major land use types include cropland (41%), forest and bush (22%), and grazing (5%). Annual rainfall is >1000 mm and mean annual temperature ranges from 15 ^{0}C in Angolelana Tera to 20 ^{0}C in Kewot (North Shewa zone Agriculture Office, 2013).

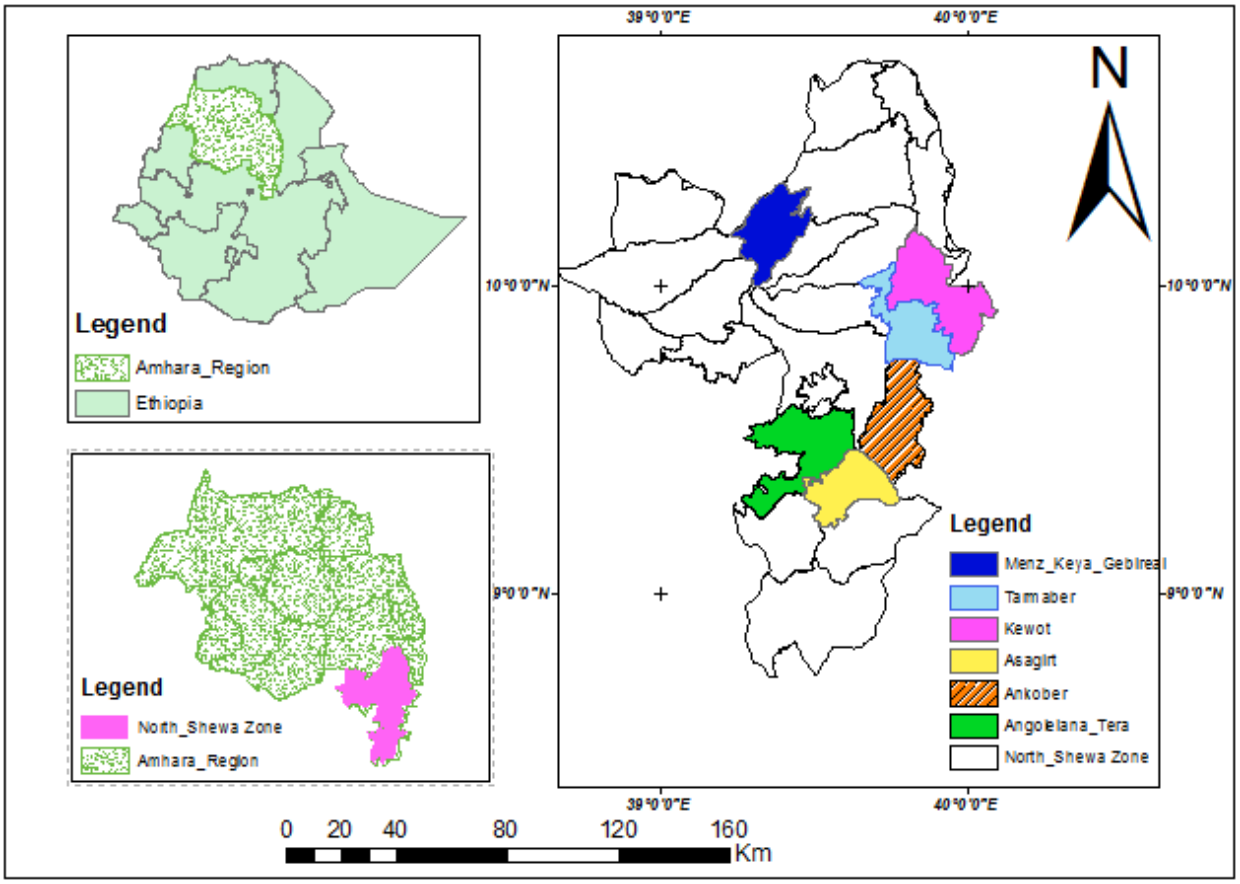

Figure 1. Geographical location of the study area and districts
Source: Extracted from Ethio-GIS, 2019.

5.2. Sampling Design

To select representative sample respondents for the household survey, multistage sampling technique was used. First, districts in the zone were clustered based on agro-ecology into three: highland, midland and lowland. Again, districts of each agro-ecological zone were classified into two based on frequency of relief recipient (high relief recipient and low relief recipient). Accordingly, from the seven districts located in the highland, three of them were high frequent relief recipients (in thirteen years, the districts received relief more than six times) and the remaining four districts were low frequent relief recipients (received relief less than or equal to six times) for the time period ranging from 2006 to 2018. Likewise, among the eleven districts which are located in the midland, three of them were high frequent relief recipients and the remaining eight districts were low relief recipients. Also, out of the four districts located in the lowland, two

districts were high frequent relief recipients and the remaining two districts were low relief recipients.

Therefore, there were six clusters of high relief and low relief recipient districts. Accordingly, from highland, Tarmaber district was high frequent relief recipient and Angolelana Tera from low frequent relief recipient clusters were randomly selected. From midland, Ankober district was high frequent relief recipient and, Asagirt and Menz Keya Gebireal from low frequent relief recipient clusters were randomly selected. From high relief recipient lowland agro-ecology districts, Kewet was also included randomly. The total districts sum up to six: two districts from highland, three districts from midland and one district from lowland agro-ecologies. Finally, representative kebeles from each district were selected using simple random sampling technique. Therefore, the total kebeles selected sum up to fifteen (eight kebeles from high relief recipient districts and seven kebeles from low relief recipient districts).

The total sample size was determined using a formula which provides the maximum size to ensure the desired precision, given by Kothari (2004) as follows:

$$n = \frac{Z^2pqN}{e^2(N-1) + Z^2pq} = 382 \qquad (1)$$

where, n is desired sample size; Z is the standard cumulative distribution that corresponds to the level of confidence with the value of 1.96; e is the desired level of precision; p is the estimated proportion of an attribute present in the population, which takes a value of 0.5 as suggested by Israel (1992) to get the desired minimum sample size of households at 95% confidence level and ±5% precision; q=1-p; and N is the size of the total population from which the sample is drawn. Accordingly, a sample of 382 household heads were selected from fifteen kebeles using random sampling method based on probability proportional to size.

5.3. Data Types, Sources and Collection Methods

The data required for achieving objectives of this study was both quantitative and qualitative in nature. For this purpose, both primary and secondary data sources were used. Primary data was collected from different category of respondents; household heads, religious leaders, local representatives, kebele leaders and experts of the study issue through questionnaire, discussion

and interview data collection instruments. To collect other relevant information, secondary data was used from various sources. Secondary data was obtained from different literature. Overall, both the quantitative and qualitative data of the study through questionnaire, group discussion and interview was conducted in the following ways;

Both closed and open-ended questions were prepared to generate the required primary household level data. Prior to the actual data collection, the questionnaire was pre-tested (April 2019) to ensure clarity, validity, and sequence of the question with the non-sampled respondents. The pre-testing was employed in three selected districts, one at each agro-ecological district. Based on the result of pre-test, necessary modifications were made and finally, the modified questionnaire was employed to collect data (April-June 2019) from the sampled households. To generate information at the field level, 20 enumerators who know the local language and hold diploma and first degree were recruited and trained on data collection tools and interview handling.

Data from Focus group discussion (FGD) and key informant interview (KII) were employed to gather general and specific information related to households' food insecurity, vulnerability and resilience situations. In relation to this, a total of three FGD were carried out, in three randomly selected kebeles, one from each agro-ecological district. The FGDs were composed of 10 participants (religious leaders, local representatives, kebele leaders, male and female household heads). A total of three individuals from three kebeles (one from each agro-ecological district) were selected as a KII. The KII was comprises of one religious leader, one expert with agricultural and environmental background and one kebele leader.

5.4. Methods of Data Analysis

Data analysis was carried out using descriptive statistics and econometric model accompanied by STATA 14 software package. Descriptive statistical tools such as mean, standard deviation, frequency and percentage, were used to describe and analyze households characteristics and level of households vulnerability to food insecurity. Econometric model was used to identify factors that contribute to households' vulnerability to food insecurity. Furthermore, mean and proportion comparison using t-test and chi-square test, respectively, were conducted to compare groups with respect to variables of interest.

5.4.1. Measurement of household vulnerability to food insecurity

Based on the definition of vulnerability given by Chaudhuri *et al.* (2002), this study considers food insecurity as a state of a household consuming less than the required threshold and uses food insecurity as a measure of welfare. Accordingly, this approach is divided into three basic steps, that is, identifying the welfare indicator; identifying the vulnerability threshold and measuring vulnerability.

Chaudhuri *et al.* (2002) uses consumption measures as a welfare indicator, arguing that it provides a more adequate picture of wellbeing, especially in low or medium-income countries. Consumption measures also have the advantage that they are accurately measured. However, rather than using mere consumption expenditure as in Chaudhuri *et al.* (2002) and Ayalneh (2012), this study employed an improved measure used by Stanley *et al.* (2015), which uses household's consumption expenditure per adult equivalent (i.e. from own production, purchases and gift/assistance) as a measure of welfare. This approach was motivated by the fact that households in the study area depended on their own production, market purchases and gift/assistance for household food consumption requirements.

The studied households commonly produce a range of crops and, livestock types and products for own consumption and selling. Therefore, the annual yields, price per kilogram, quantity sold and quantity consumed for each of crop types were obtained through the survey. The total annual expenditure on food for each household through market purchases and gift/assistance was also estimated in the survey. The questionnaire also established the total value of each livestock types and products consumed annually from own production and market purchases. The total annual household consumption expenditure was calculated by adding the annual value of crops consumed from own production, market purchase and gift/assistance, and the total value of livestock types and products consumed from own production and market purchase. The total number of household members and their age groups were also obtained from the survey. These were used to calculate the annual consumption expenditure per AE for each household.

A household with high annual consumption expenditure per AE is generally more likely to meet its consumption needs and be food secure. The daily energy requirement, as of total annual household consumption expenditure, the value of the food poverty line (threshold) recommended

by FDRE (2002), is 2200 kilocalories per AE. Therefore, using the survey result was determined. As a result, the food poverty line for the study area was found to be Birr 3463 per annum. In other words, a total of Birr 3463 per annum was needed to purchase food that could meet the basic daily food-energy requirements of an adult person. Based on the CSA (2019)'s report of the country and regional consumer price indices, the study area (North Shewa zone) had a Consumer Price Index (CPI) of 141.2% (December 2016 = 100). Thus, CPI was used to deflate the food poverty line in the study taking into account the effect of inflation. Consequently, the food poverty line is adjusted at Birr 2453 per AE per year, using the end of December 2016 constant price. These results are extensively used in the subsequent analysis of food insecurity in the present study.

The approach developed by Chaudhuri *et al.* (2002) adopted in this study identifies the vulnerability level at a given time as the probability that the household will find itself consumption poor at the next time period, and estimates this probability. The choice of the vulnerability threshold involves generating a sample that is classified into two groups, that is those that are vulnerable and those that are not vulnerable to food insecurity. It entails establishing a vulnerability threshold v, such that a household is said to be vulnerable if its vulnerability probability is greater or equal to v, that is, $v_h \geq v$. According to Chaudhuri *et al.* (2002), the choice of the vulnerability threshold is quite arbitrary. A common choice in literature is a threshold vulnerability probability of 0.5. Thus, a household was considered vulnerable to food insecurity if the probability was greater than or equal to 0.5 and less vulnerable to food insecurity if the probability was less than 0.5 (Pritchett *et al*., 2000).

Following Chaudhuri *et al.* (2002), the vulnerability level of a household h in year t is defined as the probability that the household will find itself consumption poor, that is the annual per capita value of food consumed will not be adequate to meet the recommended 2200 kilocalories per person in year t + 1. Therefore, the probability that a household will be food insecure in the future can be expressed as:

$$V_{ht} = Pr\left(C_{h,t+1} < \mathrm{Z}\right) \tag{2}$$

where V_{ht} is the vulnerability of household h to be food insecure in year t; $C_{h,t+1}$ is the food consumption expenditure per AE for a household h in year t + 1 and Z is the value of food

appropriate to meet the recommended minimum daily calorie requirement of 2200 kilocalories per AE (i.e. food security threshold).

To assess a household's vulnerability to food insecurity, there is a need to make inferences about its future consumption levels. In order to do that, a framework for thinking explicitly about both the inter-temporal and cross-sectional determinants of food availability at the household level is needed (Chaudhuri *et al.,* 2002). The food security status (i.e. annual food consumption expenditure per AE) is dependent on the household's own production, market purchases and food assistance. Consumption from own food production, agricultural and non-agricultural incomes and food assistance is influenced by a number of factors associated with adaptive capacity, risk exposure and sensitivity. This suggests the following reduced form expression for per capita annual value of food consumption expenditure:

$$C_{ht} = C(X_h) \tag{3}$$

where X_h represent a bundle of observable household characteristics including social capital, access to early warning information, access to agricultural technologies, rainfall variability, drought, flood, dependency ratio and crop diversity, among other factors. Substituting Equation (3) into Equation (2) the expression for vulnerability level is rewritten as:

$$V_{ht} = P\mathrm{r}(C(X_h) < Z|X_h) \tag{4}$$

The expression in Equation (8) suggests that the households' vulnerability level is derived from the observable household characteristics and this is compared to the household consumption expenditure per AE adequate for meeting the recommended consumption requirements (Z) (Chaudhuri *et al.,* 2002). Following Chaudhuri *et al.* (2002), Gaiha and Imai (2008) and Gunther and Harttgen (2009) who derived empirically a variant of VEP from the food consumption expenditure function, this study specifies Equation (4) as:

$$\ln C_h = X_h\beta + \varepsilon_h \tag{5}$$

where $\ln C_h$ represents the log of consumption expenditure per AE for the household, X_h represents a bundle of observable household characteristics including social capital, access to early warning information, access to agricultural technologies, rainfall variability, drought, flood, dependency

ratio and crop diversity, β is a vector of parameters to be estimated, and ε_h is a mean-zero disturbance term that captures idiosyncratic factors (shocks) that contribute to different per capita values of food consumption in different households that are otherwise observationally equivalent.

The consumption expenditure per AE for the household (C_h) is assumed to be log-normally distributed and as such the disturbance term, ε_h will be normally distributed. Furthermore, it is assumed that ε_h captures the idiosyncratic shocks that contribute to the difference in food consumption expenditure levels for households that share the same characteristics. However, it is unlikely that it captures covariate shocks which can affect all households at a given time and unexpected very large negative shocks such as food insecurity. Furthermore, it is assumed that the variance of the unexplained part of per AE value of food consumed ε_h depends on household h's observable characteristics:

$$\hat{\varepsilon}^2_{OLS,h} = X_h\theta + \eta_h \tag{6}$$

where θ represents a vector of parameters to be estimated, η_h is the vector of residuals of this second estimation. Standard regression analysis based on OLS assumes homoskedasticity, and estimates of β and θ will be unbiased but inefficient if this assumption does not hold. To deal with this problem and obtain consistent estimate of parameters, it is necessary to allow heterosckedasticity, that is, variances of the disturbance term across households depending on X_h. Thus, the estimates of β and θ could be obtained using FGLS (Chaudhuri *et al.,* 2002; Christiaensen and Subbarao, 2004; Ayalneh, 2012; Million *et al.,* 2019). In the FGLS, Equation (5) is estimated using an OLS procedure. Then the estimated residuals from Equation (5) are used as a dependent variable to estimate equation 6. The predictions from Equation (6) are used to transform equation 6 as follows:

$$\frac{\hat{\varepsilon}^2_{h,OLS}}{X_h\hat{\theta}_{OLS}} = \left[\frac{X_h}{X_h\hat{\theta}_{OLS}}\right]\theta + \frac{\eta_h}{X_h\hat{\theta}_{OLS}} \tag{7}$$

This transformed equation is estimated using OLS to obtain an asymptotically efficient FGLS estimate, $\hat{\theta}_{FGLS}$. Note that $X_h\hat{\theta}_{FGLS}$ is a consistent estimate of $\hat{\varepsilon}^2_{OLS,h}$, the variance of the idiosyncratic component of the household's food consumption expenditure per adult equivalent. The estimates;

$$\hat{\sigma}^2_{\varepsilon,h} = \sqrt{X_h \hat{\theta}_{FGLS}} \tag{8}$$

are then used to transform Equation (5) as follows:

$$\frac{\ln C_h}{\hat{\sigma}^2_{\varepsilon,h}} = \left[\frac{X_h}{\hat{\sigma}^2_{\varepsilon,h}}\right] \beta + \frac{\varepsilon_h}{\hat{\sigma}^2_{\varepsilon,h}} \tag{9}$$

OLS estimates of Equation (9) yield consistent and asymptotically efficient estimates of β. Using the estimated coefficients ($\hat{\beta} and\ \hat{\theta}$), the expected log household's food consumption expenditure per AE is measured as:

$$\hat{E}\{\ln C_h | X_h\} = X_h \hat{\beta} \tag{10}$$

and the variance of log per capita value of food consumed for each household is measured as:

$$\hat{V}\left\{\ln C_h | X_h\right\} = \hat{\sigma}_{\varepsilon,h} = X_h \hat{\theta} \tag{11}$$

Following Gaiha and Imai (2008) and Gunther and Harttgen (2009) assuming that per AE food consumption is log-normally distributed, and using the estimated parameters of the model, the probability that a household will be food insecure in the near future (say, at time t + 1) is expressed as:

$$\hat{V}_h = \hat{P}r\left\{\ln C_h < \ln \mathrm{Z} | X_h\right\} = \Phi\left[\frac{\ln \mathrm{Z} - X_h \hat{\beta}}{\sqrt{X_h \hat{\sigma}}}\right] \tag{12}$$

where $\Phi\,[\,.\,]$ is the cumulative density of the standard normal distribution function, $\hat{\sigma}$ is a variance of standard error of the regression, $\hat{\beta}$ is the expected household food consumption expenditure per AE, Z is the prescribed threshold per AE value of food consumed to meet the minimum energy requirement (food poverty line). $\hat{V}_h$ is a set of estimates one for each household and denotes the probability of falling below the minimum threshold in the future that each household faces. The value of $\hat{V}_h$ lies between 0 and 1. When $\hat{V}_h$ = 0 a household's per capita value of food consumed

will be adequate to meet the minimum amount of calories required, and when $\hat{V}_h$ = 1 the value of food consumed will be lower than the prescribed threshold.

5.4.2. Determinants of household vulnerability to food insecurity

Once the groups are categorized as vulnerable and non-vulnerable, the next step is to identify the determinants of households' vulnerability to food insecurity. Thus, various models including two-stage least squares regression model (Kakota *et al.,* 2015), three-step FGLS (Million *et al.,* 2019) and logit model (Stanley *et al.,* 2015; Arega and Woldeamlak, 2013) are often used for determining factors influencing households vulnerability to food insecurity. Therefore, this study employed the logit model following the footstep of these researchers. The dependent variable in this case, household vulnerability, was a binary variable which took a value 1 if a household was found to be vulnerable and 0, otherwise. The functional form of logit model can be specified as follows, (Pindyck and Rubinfeld, 1981):

$$\ln Y = \ln\left(\frac{Y}{1-Y}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_m X_m + \mathrm{U}_i \qquad (13)$$

where ln = natural logarithm, Y = probability of being vulnerable, 1- Y = probability of being non-vulnerable, β_m = coefficients of explanatory variables, X_m = predictor variables, and U_i = error term.

5.5. Definition of Variables and Hypotheses

After the analytical procedures are clearly delineated, it is necessary to identify the potential explanatory variables that can affect households' vulnerability to food insecurity. Consequently, theoretical and empirical literatures, and author's knowledge of the vulnerability situation of the study area were used to identify the potential determinants of households' vulnerability to food insecurity.

The dependent variable of this study is vulnerability, which is a dummy variable defined as the probability that the household will find itself consumption poor in the future, which is the annual per capita value of food consumed will not be adequate to meet the minimum daily requirement of 2200 kcal (FDRE, 2002) per AE in the future. It is determined by the present conditions, the risks potentially occurring within a defined period and the capacity to manage risks. Accordingly, a

method stated in the data analysis part of this study; which is expressed as a function of expected mean and variance of household food consumption expenditure, was used to predict the probability of households to fall below the minimum food consumption expenditure. Thus, following Pritchett *et al.* (2000), the threshold measure that is used to determine vulnerable households as those with an estimated vulnerability score greater than or equal to 0.5 was also used in the study. Consequently, households of the study have been classified as vulnerable (takes a value of 1) if the household vulnerability index is greater than or equal to 0.5 and otherwise (takes a value of 0), if not vulnerable. Based on critical review of the literature and author's knowledge of the vulnerability situation in the study area, the following explanatory variables (Table 1) were hypothesized to have an effect on households' vulnerability to food insecurity:

Table 1. Description of variables hypothesized to influence vulnerability to food insecurity

Group of influencing factors	Influencing factors	Description	Expected sign
Adaptive Capacity	Age of household head	Continuous (Years)	-
	Sex of household head	Dummy (1=Female, 0=Male)	+
	Literacy status of household head	Dummy (1=Literate, 0=Illiterate)	-
	Primary residence with iron roofed	Dummy (1=Yes, 0=No)	-
	Access to extension services	Dummy (1=Yes, 0=No)	-
	Access to early warning information	Dummy (1=Yes, 0=No)	-
	Distance to the main market	Continuous (km)	+
	Cultivated land size	Continuous (ha)	-
	Access to agricultural technologies	Dummy (1=Yes, 0=No)	-
	Livestock owned	Continuous (TLU)	-
	Social capital	Dummy (1=Yes, 0=No)	-
Exposure	Rainfall variability	Dummy (1=Yes, 0=No)	+
	Drought	Dummy (1=Yes, 0=No)	+
	Flood	Dummy (1=Yes, 0=No)	+
Sensitivity	Dependency ratio	Continuous (Percentage)	+
	Crop diversity	Continuous (Number)	-

Source: Own formulation from theoretical and empirical literatures, and authors view

6. RESULTS AND DISCUSSIONS

6.1. Estimation of household vulnerability to food insecurity

The vulnerability analysis helps to estimate the probability that the household will find itself consumption poor in the future, which is the annual per capita value of food consumed will not be adequate to meet the minimum daily requirement of 2200 kcal (FDRE, 2002) per AE in the future. Accordingly, a method stated in the data analysis part of this report was used to predict the probability of a household to fall below the minimum food consumption expenditure. Thus, following Chaudhuri *et al.* (2002), a threshold measure that is used to define vulnerable households as those with an estimated vulnerability coefficient above or equal to 0.5 was also used in the study. As a result, Table 2 summarizes the distribution of households in the study area based on level of vulnerability to food insecurity.

Table 2. The distribution of households based on level of vulnerability to food insecurity

Vulnerability Index	Vulnerability Status		
	Vulnerable (n=229)	Non-vulnerable (n=153)	Total (n=382)
Minimum	0.5	0.062	0.623
Maximum	1	0.499	1
Mean	0.705	0.304	0.545
SD	0.145	0.122	0.239

Source: Household Survey (2019).

The result of vulnerability analysis presented in Table 2 reveals that, from the sample households, 229 (59.95%) of households were found to be vulnerable to food insecurity. While 153 (40.05%) of households were non-vulnerable to food insecurity. In addition, the mean value of vulnerability index of sample households was 0.545.

6.2. Descriptive Statistics of Explanatory Variables

Several factors contribute to households' vulnerability status. This study looked at factors related to climatic shock (rainfall variability, drought and flood), factors related to sensitivity (dependency ratio and crop diversity) and factors related to adaptive capacity (age, sex, literacy status, primary residence, access to extension services, access to early warning information, distance to the main market, cultivated land size, access to agricultural technologies, livestock owned and social capital).

Accordingly, Table 3 and 4 summarize the descriptive statistics result for dummy and continuous variables, respectively, that are helpful to observe differences between vulnerable and non-vulnerable households. The chi-square value shows that there is a significant difference between the vulnerable and non-vulnerable households in terms of sex, literacy status, residence with iron roofed, access to extension services, access to early warning information, access to agricultural technologies, social capital, rainfall variability, drought and flood. The t-value shows that there is a significance mean difference between vulnerable and non-vulnerable households with respect to age, cultivated land size, livestock owned, dependency ratio and crop diversity. But, there is no statistically significant difference between vulnerability statuses of households with respect to the distance to the main market.

Table 3. Descriptive statistics for dummy variables

Variables	Category	Vulnerability status						χ^2 - value
		Vulnerable (n=229)		Non-vulnerable (n=153)		Total (n=382)		
		f	%	f	%	f	%	
Sex of household head	Male	170	55.37	137	44.63	307	100	13.62***
	Female	59	78.67	16	21.33	75	100	
Literacy status of household head	Literate	37	38.54	59	61.46	96	100	24.47***
	Illiterate	192	67.13	94	32.87	286	100	
Primary residence with iron roofed	Yes	100	42.92	133	57.08	233	100	72.15***
	No	129	86.58	20	13.42	149	100	
Access to extension services	Yes	38	32.76	78	67.24	116	100	51.29***
	No	191	71.8	75	28.2	266	100	
Access to early warning information	Yes	32	32	68	68	100	100	44.07***
	No	197	69.86	85	30.14	282	100	
Access to agricultural technologies	Yes	53	35.57	96	64.43	149	100	60.46***
	No	176	75.54	57	24.46	233	100	
Social capital	Yes	55	42.97	73	57.03	128	100	23.11***
	No	174	68.50	80	31.50	254	100	
Rainfall variability	Yes	255	80.07	56	19.93	281	100	179.25***
	No	4	3.96	97	96.04	101	100	
Drought	Yes	161	88.46	21	11.54	182	100	117.71***
	No	68	34	132	66	200	100	
Flood	Yes	143	77.72	41	22.28	184	100	46.69***
	No	86	43.43	112	56.57	198	100	

*** indicate significant at less than 1% probability level
Source: Household Survey (2019).

Table 4. Comparison of mean values for covariates based on vulnerability status

Variables	Vulnerability Status						t-value
	Vulnerable (n=229)		Non-vulnerable (n=153)		Total (n=382)		
	Mean	SD	Mean	SD	Mean	SD	
Age of household head	49.34	11.39	42.90	11.14	46.76	11.71	-5.47***
Distance to the main market	13.65	7.85	13.15	7.73	13.45	7.80	-0.61
Cultivated land size	1.00	0.41	1.39	0.48	1.16	0.48	8.39***
Livestock owned	2.56	1.48	3.31	1.59	2.86	1.57	4.70***
Dependency ratio	0.97	0.74	0.58	0.45	0.81	0.67	-5.86***
Crop diversity	2.52	1.04	3.07	1.21	2.79	1.14	4.80***

*** indicate significant at less than 1% probability level
Source: Household Survey (2019).

6.3. Determinants of household vulnerability to food insecurity

Binary logit model was used to identify the potential explanatory variables responsible for the vulnerability of households to food insecurity. Before running the analysis, variables assumed to have an influence on the vulnerability of households to food insecurity were tested for multicollinearity using variance inflation factor (VIF). The test results confirmed that there is no strong correlation among independent variables. Among 16 variables fitted into the model, sex, access to extension services, access to early warning information, access to agricultural technologies, rainfall variability, drought and crop diversity were found to be significant in determining the vulnerability of households to food insecurity. The influence of all the significant variables were in the expected direction. Table 5 provides the parameter estimates of the binary logit model.

The sign of the coefficient of sex of the household head shows a positive influence on vulnerability to food insecurity which is statistically significant at $p<1\%$. This means that the vulnerability to food insecurity is higher in female-headed households (by 39.99%) compared to those in male-headed households. The probable reason for this, as indicated in FGDs and KIIs, is female-headed households do have less access to and control over major agricultural resources even though they do much of the agricultural work. In addition, they are traditional and physically incapable of performing plowing activities, hence, they are found among the poor and, lack income and

resources that constrain their productivity. This result is in line with the results of previous studies of Kakota *et al.* (2015) and Ojo (2019).

Access to extension services was found to affect households' vulnerability to food insecurity negatively and significantly at $p<10\%$. The negative sign indicates that getting extension services reduces the risk of vulnerability to food insecurity among the sample households. This is mainly because extension services widen the households' knowledge and skill with regard to the use of improved agricultural practice and technologies. This means households who have received extension services improve their food production and livelihoods, and have better chance to be food secure in the future than those did not received. The marginal effect of the variable reveals that households having access to extension services reduces its likelihood to be vulnerable to food insecurity by 34.91%. A similar effect was observed by other studies (Mesfin, 2014b; Ojo, 2019).

The household with better access to early warning information is less likely to be vulnerable to food insecurity at $p<1\%$. The possible justification is that, households who have received or accessed weather information could reduce the risk of total crop failure, use improved seeds, invest in soil and water conservation measures and, prepare for and confront the impacts of climate extreme events. The marginal effect of the variable reveals that households having access to early warning information reduces its likelihood to be vulnerable to food insecurity by 72.17%. This result is also in agreement with the result of the study conducted in semi-arid districts of Malawi by Kakota *et al.* (2015).

Access to agricultural technologies was found to affect households' vulnerability to food insecurity negatively and significantly at $p<5\%$. This is mainly because access to technologies (e.g. improved seeds, fertilizers, pesticides, irrigation water, and veterinary services) provide an opportunity for households' to reduce the adverse consequence of weather conditions. This means households who have a range of technological options produce more, increase their income and consumption level, and diversify their copping systems than those who did not have or limited access. The marginal effect of the variable reveals that having a range of agricultural technologies decreases the likelihood of the household to be vulnerable to food insecurity by 39.03%. Jaleta *et al.* (2018) and Million *et al.* (2019) reported a similar result. They found access to technologies significantly affect households food consumption in Ethiopia.

Table 5. The logistic regression results for the determinants of household vulnerability

Variables	Coef.	Std. Err.	z	P>z	Marginal effect
Age of household head	0.0188	0.0310	0.61	0.545	0.0041
Sex of household head	2.8164	1.0426	2.70	0.007***	0.3999
Literacy status of household head	-1.0949	0.6896	-1.59	0.112	-0.2523
Primary residence with iron roofed	-0.8276	0.6383	-1.30	0.195	-0.1716
Access to extension services	-1.5353	0.8948	-1.72	0.086*	-0.3491
Access to early warning information	-3.6518	0.8968	-4.07	0.000***	-0.7217
Distance to the main market	0.0656	0.0486	1.35	0.177	0.0142
Cultivated land size	-0.4254	0.7271	-0.59	0.559	-0.0920
Access to agricultural technologies	-1.7792	0.8396	-2.12	0.034**	-0.3903
Livestock owned	-0.1441	0.1969	-0.73	0.464	-0.0312
Social capital	-0.9993	0.6131	-1.63	0.103	-0.2248
Rainfall variability	12.4880	2.4119	5.18	0.000***	0.9830
Drought	5.9168	1.1435	5.17	0.000***	0.8653
Flood	-1.0281	0.6387	-1.61	0.107	-0.2209
Dependency ratio	0.0813	0.5503	0.15	0.882	0.0176
Crop diversity	-1.2048	0.3520	-3.42	0.001***	-0.2606
Cons	-5.6858	2.1906	-2.60	0.009	
Log likelihood	-45.3819				
Number of obs	382				
LR χ^2 (16)	423.58				
Prob > χ^2	0.0000				
Pseudo R^2	0.8235				

***, ** and * indicates significant at less than 1%, 5% and 10% probability levels, respectively
Source: Household Survey (2019).

Rainfall variability was found to affect households vulnerability to food insecurity positively and significantly at p<1%. The positive effect indicates that the occurrence of rainfall variability increases the risk of vulnerability to food insecurity among farm households. This is due to the fact that frequent rainfall variability could result in crop failure that impedes the availability of food and reduce income that the households could have earned from their production. The marginal effect of the variable reveals that as the experience of rainfall variability increases, the likelihood of the household to be vulnerable to food insecurity will increases by 98.3%. A similar effect was reported by Demeke *et al.* (2011) and Mesfin (2014a).

Drought was significantly and positively affect households vulnerability to food insecurity at p<1%. The positive effect indicates that the occurrence of drought increases the risk of

vulnerability to food insecurity among farm households. The possible explanation is that frequent drought could result in crop failure that impedes the availability of food and reduce income that the households could have earned from their production. The marginal effect of the variable reveals as the experience of drought increases, the likelihood of the household to be vulnerable to food insecurity will increases by 86.53%. A similar effect was observed by Mesfin (2014a, b).

The result of logit model showed that crop diversity has significant (at $p<1\%$) and negative influence on households vulnerability to food insecurity. This means that an increase in the number of crops cultivated decreases the likelihood for the household to become vulnerable to food insecurity. This is possible because as farm households cultivate various crops on a given farm plot, improve food stocks in terms of quantity and variety and also improve income through sale of crop produced which then is used to further improve consumption patterns. This result agrees with the prior expectation. The marginal effect of the variable indicates that the probability of the household to be vulnerable to food insecure will decrease by 26.06% when the number of crop types cultivated across all farm plots increase by one unit. A similar influence was also reported by Ayalneh (2012).

6.4. Classification and decomposition by vulnerability and food insecurity status

Considering both the vulnerability status of households and its current food insecurity status, the study extended the analysis into several food insecurity and vulnerability categories as shown in Table 6. First, households may be classified as of vulnerable or non-vulnerable according to whether the vulnerability index is ≥ 0.5 or <0.5, respectively (Pritchett *et al.,* 2000). Second, the sample households may be divided into two distinct groups using the measure of food poverty line. In this regard, a household was considered as food insecure when the per capita food consumption expenditure (PCFCE) was less than the threshold level; otherwise, the household was inferred as food secure.

The results indicate that about 27.49% of the sample households had stable food security levels. These households were food secure and had low probabilities of being food insecure in the near future (less vulnerability to food insecurity). On the other hand, about 43.72% of the total households were categorized as food insecure for an extended period of time and were considered as suffering from chronic food insecurity. They had PCFCE values which were below the threshold

level with probabilities of being food insecure being greater than or equal to 0.5. These were considered as being highly vulnerability to food insecurity, and having little chance of escaping from food insecurity in the near future. According to FAO (2008), these households may need a special attention in terms of direct food assistance and access to productive resources which will enable them to improve their productive capacity and help them escape from food insecurity in the near future.

In addition, about 12.57% of the total households were considered as suffering from transient food insecurity, which means that even if they had current PCFCE values of less than the value of food poverty line, they were less likely to fall into food insecurity in the near future and could totally escape from food insecurity. Moreover, about 16.23% of the total households were grouped under the transient food security category, meaning that these households may face a sudden drop in their ability to access adequate and sufficient food, hence fail to maintain good nutritional status in the near future. Those households had access to adequate food but were highly vulnerable to food insecurity. This implies that they were more likely to become food insecure in the future. Furthermore, about 28.8% of the total households (12.57 + 16.23%) were categorized as having an unstable food insecurity status. Overall, these findings imply that households were recurrently moving into and out of the state of being food insecure which has a particular policy implication, that is, vulnerability to food insecurity should be viewed in a broader manner as not only entailing households vulnerability to food insecurity (those who are chronically food insecure), but also those who are currently food insecure but less likely to be vulnerable to food insecurity as well as those who are currently food secure but highly likely to be vulnerable to food insecurity in the near future. In this study, these households constituted about 72.52% of the total households.

Table 6. Classification and decomposition by vulnerability and food insecurity status

	Food Insecurity Status				χ^2 - value	Total (n=382)	
	Food Insecure (n=215)		Food Secure (n=167)				
	No.	Percent	No.	Percent		No.	Percent
Vulnerability status							
Vulnerable	167	43.72	62	16.23	64.36***	229	59.95
Non-vulnerable	48	12.57	105	27.49		153	40.05
Total	215	56.28	167	43.72		382	100

***indicate significant at less than 1% probability level
Source: Household Survey (2019).

7. CONCLUSIONS AND POLICY IMPLICATIONS

From vulnerability analysis, it can be concluded that access to adequate and sufficient food is unstable in the study area. This means that many households food insecurity status vary over time and dynamic nature. This, in turn, implies that food security policies and strategies should be based equally on the assessment of households' current conditions as well as on the expectations of their future access to food. Based on this conclusion, the study recommends the establishment and strengthening of appropriate service providers (such as institutions that provide agricultural extension services, early warning information, and affordable agricultural technologies to farm households). In addition, proper policy and strategy should be formulated to safeguard farm households from the negative effect of climate extremes (for example rainfall variability and drought). Introducing the notion of environmental conservation activities and giving training on its application. Moreover, the current efforts by the regional and local governments to intensify promotion of crop diversification should remain a priority policy direction due to the continued food insecurity threat. This is particularly so in this era of climate variability that poses an extra burden to farm households of the study area.

Declarations

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Authors' contributions
Conceptualization: Debebe Cheber; Methodology: Debebe Cheber; Software: Debebe Cheber; Validation: Fekadu Beyene, Jema Haji and Tesfaye Lemma; Formal Analysis: Debebe Cheber; Investigation: Debebe Cheber, Fekadu Beyene, Jema Haji and Tesfaye Lemma; Resources: Debebe Cheber; Data Curation: Debebe Cheber, Fekadu Beyene, Jema Haji and Tesfaye Lemma; Writing – Original Draft Preparation: Debebe Cheber; Writing – Review & Editing: Debebe Cheber, Fekadu Beyene, Jema Haji and Tesfaye Lemma; Visualization: Debebe Cheber; Supervision: Fekadu Beyene, Jema Haji and Tesfaye Lemma; Project Administration: Debebe Cheber; Funding Acquisition: Debebe Cheber.

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Availability of data and materials

Data that support the findings of this study are available upon request through the corresponding author.

Competing interests
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Authors' information
[1] Department of Rural Development and Agricultural Extension, Jimma University, Ethiopia
[2] School of Rural Development and Agricultural Innovation, Haramaya University, Ethiopia
[3] School of Agricultural Economics and Agribusiness Management, Haramaya University, Ethiopia

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