Journal of Sustainable Development in Africa (Volume 26, No.1, 2024)
ISSN: 1520-5509
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DETERMINING THE STATUS OF FOOD INSECURITY OF HOUSEHOLDS IN *PROSOPIS JULIFLORA* (SWARTZ DC.) INVADED AND NON-INVADED AREAS IN AFAR REGION

AN APPLICATION OF THE RASCH MODEL

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ABSTRACT

Food security in an integral part of sustainable development. This study aimed to assess food security in Prosopis-invaded and non-invaded districts (Amibara and Awash Fentale, respectively) in the Afar region, where the availability and efficient utilization of natural resource is very critical sustainable livelihood of the community. Employing the Rasch modeling approach and using Food Insecurity Experience Scale (FIES), data from 438 randomly selected households collected in 2022 were analyzed. Results indicated that a lower average food security assessment in Amibara (5.168 ± 0.8) compared to Awash Fentale (6.576 ± 3.575), at a 5% significance level. Results also revealed significantly higher food insecurity prevalence in Amibara (Prosopis invaded) compared to Awash Fentale. The analysis also showed 50% and 43% of households as severely food insecure in invaded and non-invaded areas, respectively. Additionally, 47% and 30% of households were moderately food insecure in invaded and non-invaded areas, respectively. Notably, only 3% of the households are food secure in the invaded area, while 28% were food secure in non-invaded areas. Thus, the study underscore the treat the invasion posed and hence urgent on the need for targeted interventions to address the invasion and food insecurity in these communities.

Keywords: Rasch model, severity, prevalence, invaded and non-invaded, food insecurity.

INTRODUCTION

Food security and nutrition is an integral part of sustainable development (Berry et al, 2015). The environment and the obtainability of natural resources are preconditions for the availability of food as well as the preservation of biodiversity (Sperling & McGuire, 2012; Berry *et al*, 2015). One of the ecological challenges in arid and semi-arid area in Ethiopia is the invasion of exotic plant species that pose significant threat to natural ecosystems and environmental sustainability, particularly in areas experiencing severe depletion of resources like soils, water, and forests. At first, people are compelled to introduce new exotic plant species, chosen for their ecological adaptability and rapid growth as an effort to reduce desertification. However, research indicates that the adverse ecological and social impacts of many invasive plants often outweigh their benefits (Pasiecznik et al., 2001). Notably, Prosopis juliflora is recognized as one of the most invasive alien plant species, impacting pastoralists and agro-pastoral livelihoods in Ethiopia's Afar Region. This invasion disrupts daily activities, affecting the livelihoods of pastoralists and the broader ecosystem in the region. Despite some potential benefits, the prevailing perception among the local population overwhelmingly leans toward viewing Prosopis juliflora as harmful, often referred to as the "devil tree."

The invasive plant has caused disruptions to ecosystems, biodiversity, health, socioeconomic, and various aspects of human welfare often impacting livestock productivity in the area by limiting pasture availability in invaded rangelands (Pasiecznik et al., 2001). Livestock, crucial for nutrition, food security, livelihoods, and resilience for millions globally, face a decline in numbers as households sell animals to purchase food. For instance, in rural Afar, approximately 64% of households consume less than three out of seven food groups, contributing to a precarious food situation (Ethiopia & Headquarters, 2014; Ilukor et al., 2016a). Notably, the Afar region experiences the highest food expenditure and malnutrition, coupled with the lowest household food stock per capita (1 kg/person) in the country (WFP, 2009).

Globally, 9.7% of the world population (746 million or nearly one in ten people in the world) were exposed to severe levels of food insecurity in 2019, with an additional 16% facing food insecurity at moderate levels (FAO, IFAD, UNICEF, WFP and WHO, 2020). In Ethiopia, the Ethiopia & Headquarters (2019) estimate shows that 25.5% of the people experiences food insecurity, with varying levels across regions. Notably, the Amhara region reports the highest percentage of food insecure households at 36.1%, followed by Afar (26.1%) and Tigray (24.7%). Rural areas exhibit a higher food insecurity rate of 22.7% compared to urban areas at 13.9%. In Afar, the average monthly household expenditure is 775 birr (Ethiopia & Headquarters, 2019). A study by Hirvonen & Wolle (2019) in Afar revealed concerning findings: none of the rural children and only 10.1% of urban children met the minimum dietary needs. Additionally, only 11% of households in Afar consumed from more than six food groups, where total calorie declined by 6% between 2012 and 2015. Food insecurity manifests in various stages, from initial concerns about having enough food to dietary changes and prolong food availability. This progression often involves reducing consumption sizes, starting with adults and extending to children (Meroni et al., 2017).

Over the past two decades, an increasing number of pastoralists in Afar have shifted from a pastoral to sedentary lifestyle, engaging in alternative income-generating activities (Ilukor et al., 2016b; Rettberg, 2010; Rettberg & Müller-Mahn, 2012) even though there are limited livelihood diversification options to tackle food insecurity challenges in Afar region which is facing the invasive plant species. Previous studies on *Prosopis juliflora* primarily focused on various aspects including its expansion, ecological impact, environmental consequences, and potential utilization. Although some studies delved into the biological characteristics fostering its invasive nature and effects on ecological services, there is limited attention to assessing the specific impact of *Prosopis juliflora* invasion on the food security of pastoralists and agro-pastoralists in the region. This paper attempted to address this gap by conducting a focused assessment to understand the impact of *Prosopis juliflora* invasion on food insecurity severity, comparing invaded and non-invaded areas using FIES data and applying the Rasch model.

METHODOLOGY

Study Sites

The study was conducted in the Afar Regional State (ANRS), specifically in *Awash Fentale* and *Amibara Woredas,* located at approximately 40°08'-40°12'E and 09°16'-09°21'N, situated 160 km and 250 km from Addis Ababa, respectively (Figure 1). The Afar National Regional State is situated within the Great Rift Valley of East Africa, covering 6.67 million hectares, accounting for about 10% of Ethiopia's total land area and approximately 29% of pastoral lowlands (Shiferaw et al., 2019). The region experiences arid and semi-arid conditions, with a mean annual temperature of 31 °C and erratic rainfall ranging between 200 and 600 mm annually. The population of the region is around 1.99 million (CSA, 2021). *Amibara* and *Awash Fentale Woredas* have total populations of 110,427 and 55,708, respectively, with rural populations of 86,133 (14,355 households) and 43,452 (7,242 households), respectively. The average household size is seven (CSA, 2021). The livelihood system in the region predominantly relies on pastoralism (over 90%) and agro-pastoralism (less than 10%), with some engagement in small-scale irrigation activities along the rivers.

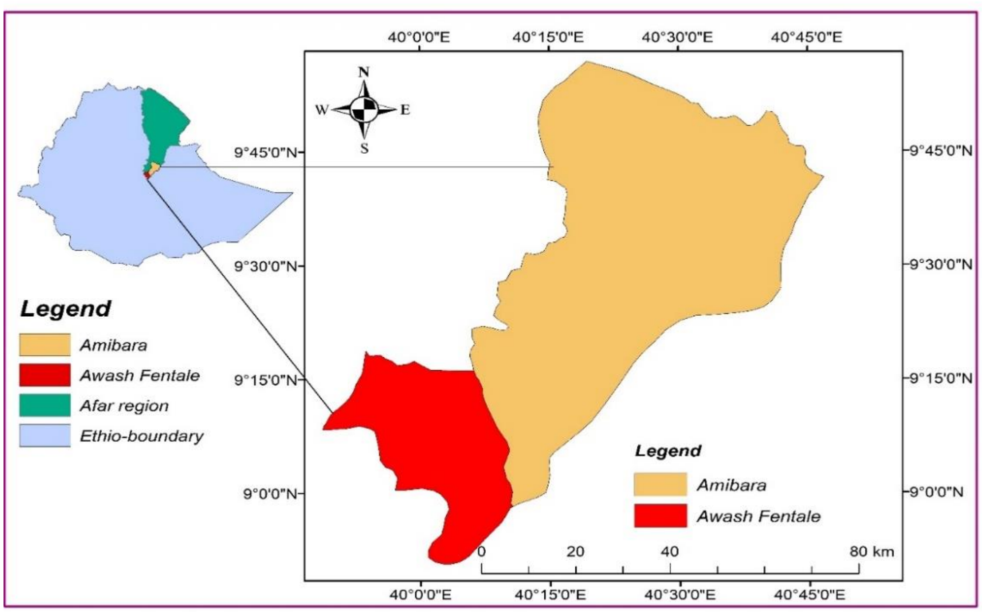


Figure 1: Map of study sites, Afar region, Ethiopia

Sampling Methods

This study employed a multi-stage sampling method to select the study region, districts (woredas) and *kebeles*[1]. Firstly, Afar region was purposively chosen, and amongst the woredas in the region, *Amibara* and *Awash Fentale woredas* were selected due to their distinct status in Prosopis juliflora invasion. *Amibara woreda* is one of the first *woredas* invaded by Prosopis juliflora in Afar, while *Awash Fentale* is relatively unaffected. Subsequently, specific Prosopis juliflora invaded and non-invaded *kebeles* were purposively selected within these *woredas*. Accordingly, *Bedul Ali, Halaydege, Serkamo* and *Worer kebeles* were chosen from invaded areas whereas *Doho, Dudub, Kebena* and *Sabure kebeles* were selected from *Awash Fentale woreda*. A random sample of pastoralist and agro-pastoral households was then selected based on probability proportionate to the relative size of households in the chosen *kebeles*. In cases of refusal to participate in the interview, households were replaced sequentially. Data collection utilized a pre-tested survey questionnaire administered by experienced local language speakers using the Kobo toolbox system on mobile/tablet devices. Additionally, a desk review was conducted, incorporating information from various sources to develop a comprehensive survey questionnaire.

Sample Size

The sample size for this study is determined by employing Yamane (1973) formula that enabled to calculate the sample size from each *woredas* of the rural population. The sample size calculation has considered a 5% acceptable error (e=0.05) and a 95% confidence level. The formula is given as:

$$n = \frac{\mathrm{N}}{(1+\mathrm{N}\,(e^2)} \qquad \text{(1) (Yamane, 1973)}$$

Where: n = desired sample size

N = total number of population (i.e. HHs)

e = the level of precision or the quality of being careful and accurate which is equal to 0.05.

Hence, the data were collected from a total sample of 438 households from the two woredas (224 and 214 households from Amibara and Awash Fentale woredas, respectively).

DATA COLLECTION METHODS AND SOURCES

The study used both primary and secondary sources. The primary sources are mainly the pastoralists and agro-pastoralists in the study area. Primary data collection tools, including well-designed survey questionnaire (i.e. the Food Insecurity Experience Scale (FIES)) was used for this study. This field-level data were gathered during the lean season (January and February 2022). The researcher employed a combination of quantitative and qualitative surveys at the household/individual level, utilizing mainly key informant interviews and focused group discussions for the qualitative part. And the primary data source are complemented with secondary data sources including various published materials.

The Food Insecurity Experience Scale (FIES) tool has consisted of eight questions that helped to measure the food security status of households in both P. juliflora invaded and non-invaded sites. FIES utilizes dichotomous responses ("yes"/"no") to

[1] *Kebele* is the lowest administrative division in Ethiopia.

compute valid indicators of food insecurity prevalence and severity. Respondents' answers are aggregated to generate raw scores ranging from 0 to 8, with food insecurity classified into three categories: 1) Food Secure (FS) with raw scores ranging from 0 – 3; 2) Moderate Food Insecurity (MFI) with raw scores of 4 – 6; and 3) Severe Food Insecurity (SFI) with raw scores of 7 – 8. FIES provides an experience-based metric for assessing the severity of food insecurity conditions of the households (Ballard et al., 2014; Cafiero et al., 2016; Saint Ville et al., 2019).

In general, the underlying premise of the Food Insecurity Experience Scale (FIES) is that the severity of food insecurity within a household or individual can be treated as a latent trait encompassing behavior, experiences, and perceptions. Latent traits, though not directly observable, can be deduced from observable evidence using measurement models based on Item Response Theory (IRT). This statistical approach is more versatile in gauging food insecurity compared to traditional methods relying on indirect assessments through determinants (like food availability) or consequences (such as anthropometric failures and signs of malnutrition) (Ballard et al., 2014; Cafiero et al., 2016; Nord, 2014).

The FIES module comprises items directly questioning individuals about compromises in the quality and quantity of their food due to limited financial or resource means. Each FIES question pertains to a distinct situation, associated with a specific severity level (Ballard et al., 2014; Nord, 2014). FIES goes beyond other measures by capturing psychosocial effects in certain community groups (e.g., women and children), reflecting anxiety or uncertainty regarding the ability to procure sufficient food (Wambogo et al., 2018). Thus, FIES was utilized in this study to determine the prevalence of food insecurity in areas invaded and non-invaded by Prosopis juliflora.

Data Analysis Methods: Rasch Model and its Applications

The status and severity of food insecurity of households among the two sites (invaded and non-invaded) was examined using the Rasch modelling approach. The Rasch Model, also known as the one-parameter logistic (1PL) model is used to gauge the severity of food insecurity based on responses to experience-based FIES questions in individual households (Ballard et al., 2014; Boone, 2016; Nord, 2014; Rosenbaum & Rubin, 1983). This model, named after the Danish mathematician Georg Rasch, assumes that households are more likely to affirm less-severe items than more-severe ones and that items are more likely to be affirmed by households experiencing greater food insecurity (Deitchler et al., 2010). Key assumptions of the Rasch Model include equal item discrimination, indicating each item is equally associated with the measured construct; and conditional item independence, suggesting that items are correlated only due to their association with the latent trait and they are conditionally independent and unidimensional (Nord, 2014; Wambogo et al., 2018).

In the Rasch model, item difficulty and respondent ability are the underlying variables measured, where respondent ability represents the severity of food insecurity, and difficulty implies the severity inferred by an affirmative response (Opsomer et al., 2002). The model assumes an unobservable, one-dimensional, and continuous trait—referred to as ability—that all respondents possess to varying degrees. The model conceptually establishes a continuous scale for item difficulty and respondent ability. In food insecurity studies, each respondent answers dichotomous FIES questions based on their latent ability where higher ability increases the probability of a positive response. The Rasch model allows simultaneous estimation of individual ability and item difficulty parameters. It assumes that the trait being measured is unobservable but can be assessed by questions whose likelihood of an affirmative response is directly related to the strength or severity of that trait (Opsomer et al., 2002). The Rasch model assumes that if the wording of an item remains constant, its estimated severity should remain consistent over time. Thus, households experiencing a certain level of food insecurity in one year are expected to respond to each item similarly in subsequent years (Owino, Wesonga, and Nabugoomu et al., 2014; Owino et al., 2016). Measurement of food insecurity is challenging due to its multifaceted and continuous nature influenced by numerous variables (Owino et al., 2014; Owino et al., 2016).

The simple Rasch model employs a logistic function to model the probability of a correct response based on the difference between person and item parameters (Elijah, 2010). It formalizes the concept of severity ordering of items, allowing the estimation of item and household severity and assessing response consistency with this concept (Nord, 2014). Food insecurity, a latent trait, lacks a standardized language for description. It is a latent trait, i.e., not directly observable. People do not say, “On a scale of 1 to 10, my food insecurity is at level 3”. But people do speak readily about specific experiences such as running out of money for food, and the specific behaviors and conditions that result it such as being forced to cut back on quality or quantity of food. The Rasch model utilizes well-designed survey questions to elicit information about specific experiences, behaviors, and conditions related to food insecurity (Nord, 2014).

The one-parameter Rasch model (Rasch, 1960) predicts the probability of selecting the correct response of a test item depending on a latent trait θn. For multiple-choice items and short-answer items with a category score 1 for correct responses and 0 for incorrect responses, and this is modelled as equation (2) below:

$$P_i(\theta) = \frac{\text{Exp}(\theta n - \delta i)}{1 + \text{Exp}(\theta n - \delta i)} \qquad \text{(2) (Wolfram } et\ al.\text{, 2011)}$$

Where, $P_i(\theta)$ = the probability of person n to score 1 on item *i*,

θ_n = the estimated latent trait of person *n*, and

δ_i = the estimated location of item *i* on this dimension. And for each item, item responses are modelled as a function of the latent trait θ_n.

In Rasch model, the probability that a respondent report a given experience is a logistic function of the distance between the respondent’s and the item’s positions on the severity scale. In this case, it is given by the equation (3):

$$\text{Prob}\,(xh, = 1|\theta h) = \frac{e^{\theta h - \beta i}}{1 + e^{\theta h - \beta i}} \qquad \text{(3) (FAO, 2016)}$$

Where, $xh,$ = the response given by respondent h to item i, coded as 1 for “yes” and 0 for “no” (more severe experiences are reported by fewer respondents),

β_i = the relative severity associated with each of the experiences, and

θ_h = how many of the items responded affirmatively.

Furthermore, the Rasch model that the log odds of a household (V) responding to an item (i) correctly are a function of ability (θV) and the item’s difficulty (β_i). We can state this model as difficult items are hard to get right even for people with high ability. The odds of getting an item right decrease with item difficulty and thus the minus sign before β_i. And, this is depicted on the equation (4) and (5) as:

$$\text{Logit}\ (Pi,\ \text{V}) = \log\frac{\Pr\ (\text{Pi,V})}{1 - \Pr\ (\text{Pi,V})} = \theta\text{V} - \beta i \qquad \text{(4) (Abraham } et\ al.\text{, 2014)}$$

Where, V = 1, 2, . . . , number of households/respondents,

i = 1, 2, . . . , number of items, and

θV = normally distributed random variable with zero mean and variance τ.

$$\text{Prob}\ (x\text{v}, =\frac{1}{\theta\text{v}}, \beta i) = \frac{exp(\theta\text{V} - \beta\text{i})}{1+exp(\theta\text{V} - \beta\text{i})} \qquad \text{(5) (Abraham } et\ al.\text{, 2014)}$$

Where, V = 1, 2. . . n are the households [n (*Amibara)* = 224, n (*Awash Fentale)* = 214],

i = 1, 2, . . . , m (m = 8 items/questions) are the items,

XVi = household (V) gives correct response to item (i),

θV = the ability of household (V) to give correct response to item (i), and

β_i = the difficulty level of item (i).

In addition, the Rasch model's data fit is assessed using infit and outfit statistics for each item. Infit statistics measure the information-weighted mean square residuals between observed and expected responses, while outfit statistics, more sensitive to outliers, serve a similar purpose. Values close to 1 indicate satisfactory fit, while values exceeding 1.5 or falling below 0.5 are considered misfit. Infit values between 0.8 and 1.2 are excellent, 0.5 to 1.5 are acceptable, and values above 1.5 warrant investigation, particularly for potential translation issues in subsequent years (Cafiero et al., 2016; Rasch, 1960). Positive Rasch model values classify households as food secure, while negative values classify them as food insecure (Abraham *et al.*, 2014). Hence, the food insecurity and severity level of households in prosopis-invaded and non-invaded sites was analyzed using this model.

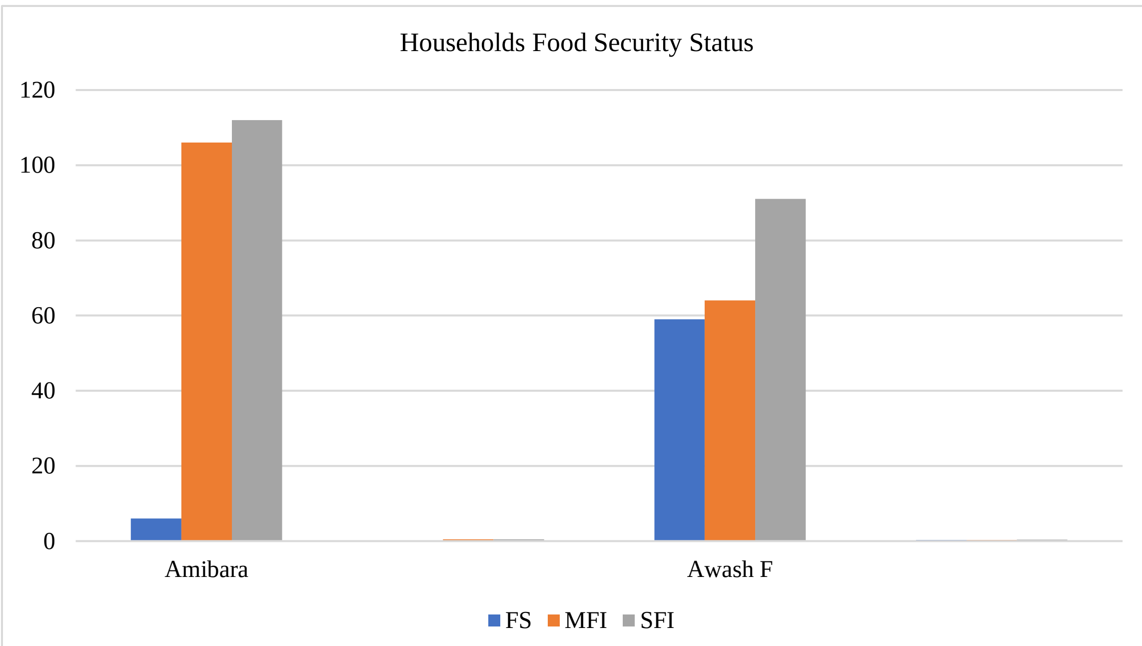
RESULTS AND DISCUSSIONS

Descriptive Statistics

The difference in households' food insecurity can be explained by a range of socioeconomic characteristics of households, such as income, education, employment status, and household size and others. Generally, households with lower incomes, lower levels of education, and fewer employment opportunities are more likely to experience food insecurity and lower levels of welfare (Loopstra & Tarasuk, 2013). On the other hand, households with higher incomes, higher levels of education, and better employment opportunities may have better access to a wider range of food options and better status of food security.

The inferential analysis entails that there is a difference between the invaded and non-invaded areas on some socio-economic variables namely: age, distance from the market, access to veterinary services, and marital status. Besides, the analysis of the food security status of households of both *Prosopis juliflora* invaded and the non-invaded area using the food insecurity experience scale (FIES) revealed that 50% and 43% of the sample households were severely food insecure (SFI) in invaded and non-invaded areas respectively (Figure 2). Similarly, 47% and 30% of the households are moderately food insecure in invaded and non-invaded sites. In addition, the analysis revealed that only 3% of the households are food secure in invaded area whereas about 28% of the households are food secure in non-invaded areas. The high severity of food insecurity in the invaded area might be due to the impact of the Prosopis invasion and its related negative effect on the livelihood system especially on the productivity of crop and livestock in the *woreda*.

Figure 2: Households Food Security Status by districts



The FIES method contained eight questions (Table 1) and the reference period for all questions spans the 12 months preceding the interview day. Binary coding was applied to responses, where "yes" corresponds to 1 and "no" to 0 for yes/no responses. The analysis reveals that the average food security assessment for *Amibara* district is 5.168 with a margin of error of ±0.8, while for Awash district, the average is 6.576 with a larger margin of error of ±3.575, both measured at a five-percentage level of significance (Table 2). Comparatively, households in Awash district exhibit a higher level of food security than those in *Amibara* district. The standard errors indicate a notable difference in precision between the two districts. The confidence interval for *Amibara* district spans from negative to positive values, suggesting that, on average, food insecurity of households in *Amibara* district tends to be higher than in households in Awash district.

Table 1: Eight FIES questions - Study variables

Short reference	Question in word
WORRIED	**1. The last 12 MONTHS was there a time when** … You were worried you would not have enough food to eat because of a lack of money or other resources?
HEALTHY	**2.** You were unable to eat healthy and nutritious food because of a lack of money or other resources?
FEWFOODS	**3.** You ate only a few kinds of foods because of a lack of money or other resources?
SKIPPED	**4.** You had to skip a meal because there was not enough money or other resources to get food?
ATELESS	**5.** You ate less than you thought you should because of a lack of money or other resources
RANOUT	**6.** Your household ran out of food because of a lack of money or other resources.
HUNGRY	**7.** You were hungry but did not eat because there was not enough money or other resources for food?
WHLDAY	**8.** You went without eating for a whole day because of a lack of money or other resources.

Table 2: Descriptive statistics for household food security for *Amibara* and *Awash Fentale* districts

Household score on food security scale		
Descriptive statistics	***Amibara***	***Awash Fentale***
Mean	5.168	6.576
Standard error	0.199	0.097
Median	6	6
Mode	7.783	7.990
Standard deviation	2.913	1.453
Sample Variance	8.488	2.111
Kurtosis	-0.9845	-0.668
Skewness	-0.666	-0.543
Range	8	6
Minimum	0	2
Maximum	8	8
Largest (10)	8	8
Smallest (10)	0	2
Confidence interval (95%)	0.8	3.575

Source: Own survey, 2023

FOOD INSECURITY STATUS: RESULTS FROM RASCH MODEL ESTIMATES

The item parameters derived from the collective response patterns of the participants is shown on Table 3 below. These parameters reflect the relative severity (difficulty) of each item within the context of the application of FIES, along with their corresponding standard errors. A lower item parameter value indicates a less severe experience associated with the respective question, whereas a higher item parameter value suggests a more intense or severe experience. The analysis of the Rasch model focused on eight items deemed influential in determining food security within the *Amibara* and *Awash Fentale* districts. Coefficients were computed for difficulty level parameters, as illustrated in Tables 3. Accordingly, the item with the highest severity, indicating the fewest "yes" responses or less likely to be reported by respondents is *WholeDay*, and hence, the severity level in *Amibara* is notably higher compared to *Awash Fentale*. This indicates that the level of food insecurity of households in prosopis invaded area is significantly higher (10%) than in non-invaded area - *Awash Fentale*.

Table 3: Estimated theta coefficients of the Rasch model for *Amibara* and Awash districts

	Theta (difficulty parameter level) estimates			
	Estimate for *Amibara* (Severity)	S.E.	Estimate for *Awash Fentale* (Severity)	S.E.
Fewfood	-3.378248149	0.635559455	-4.651675435	1.030089 *
Skipped	-2.314321897	0.463543542	-1.96271086	0.509972 ***
AteLess	-0.817549307 ***	0.307803092	0.09521124	0.314011 ***
RunOut	0.908564453 ***	0.24288924	1.319154347	0.280417 ***
Hungry	2.515990295 ***	0.294113978	2.296908943	0.302322 ***
WholeDay	3.085565269 ***	0.353244969	2.903112565	0.342983 ***

Sign. Codes: ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05

Source: Own survey, 2023

Infit/outfit statistics

The Infit/Outfit good range values between 0.7 – 1.3 are considered acceptable. When an item fits the model perfectly, the Infit/Outfit value equals one. Infit value above 1.0 indicates that the item discriminates less sharply than the average of all items in the scale while Outfit value above 1.0 indicates a weaker than average association of the items with the underlying conditions (Owino et al., 2016). Values between 0.5 and 1.5 and are therefore good for productive measurement (Owino et al., 2016). Values above 1.5 suggested inconsistent performance, while those below 0.5 indicated insufficient variation, in accordance with the works of (Rasch, 1960; Wright & Masters, 1982). Notably, outfit statistics are particularly responsive to extreme scores. Accordingly, we assessed how well responses to items correspond to the Rasch model assumptions by calculating “infit” and “outfit” through the infit and outfit statistics (Table 4). The results showed that five of the items (FEWFOOD, SKIPPED, ATELESS, HUNGRY AND WHOLEDAY) in *Amibara* and six of the items (HEALTHY, FEWFOOD, SKIPPED, ATELESS, HUNGRY AND WHOLEDAY) in *Awash Fentale* are performed well and within usual fit criteria (0.5- 1.5). After repeated check about the performance of items to measure the food insecurity, it was found that two items i.e WORRIED and HEALTHY didn’t perform well in the given population of *Amibara* as a result these two items are dropped from both districts from further analysis as the number of respondents who answers yes (N_Yes) are not few (Table 4) and not good to ignore this and retain the items in the scale to estimate the food insecurity prevalence of the study sites (Cafiero et al., 2018).

Table 4. Infit/outfit test result for eight FIES items

	Amibara						*Awash Fentale*					
Items	**Severity**	**S.E.**	**Infit**	**S.E Infit**	**Outfit**	**N_Yes**	**Severity**	**S. E**	**Infit**	**S.E infit**	**Outfit**	**N_Yes**
Worried	-0.931	0.509	1.581	0.382	18.197	121.00	-3.500	0.475	1.491	0.258	47.622	100.00
Healthy	-10.111	41.726	0.000	41.723	0.000	126.00	-3.338	0.460	0.571	0.246	0.128	99.00
Fewfood	-1.176	0.556	0.952	0.427	2.715	122.00	-2.392	0.416	0.824	0.232	0.270	92.00
Skipped	-0.242	0.406	0.928	0.295	7.352	117.00	-0.871	0.399	0.538	0.295	0.214	80.00
AteLess	1.047	0.284	0.674	0.190	0.967	103.00	1.036	0.301	1.048	0.183	1.552	60.00
RunOut	2.671	0.226	0.439	0.126	0.433	63.00	2.216	0.272	0.654	0.136	0.605	39.00
Hungry	4.159	0.266	0.913	0.162	1.220	22.00	3.150	0.291	1.009	0.150	0.955	22.00
WholeDay	4.583	0.299	0.565	0.195	0.302	15.00	3.698	0.322	1.039	0.180	0.845	14.00

Source: Own calculation from survey, 2023

Reliability

Rasch reliability is a measure of the consistency and stability of responses to items in a test or assessment. It assesses how well observed data align with the model's expectations. The Rasch model assumes that the probability of a person endorsing an item (e.g., answering a question correctly) depends on the person's ability and the difficulty of the item. The Rasch reliability index indicates the extent to which the observed responses align with the expected responses predicted by the model. After dropping of the two unfit items, the reliability of the Rasch model for the six items is tested and found within the acceptable limit i.e. ***0.75*** (Table 5 & 6).

Table 5: Rasch reliability and residuals correlation (*Amibara*)

Rasch reliability					
0.75					
Residual correlation					
	SKIPPED	ATELESS	RUNOUT	HUNGRY	WHOLDAY
FEWFOOD	-0.08	0.09	-0.02	-0.27	-0.36
SKIPPED		0.00	-0.13	-0.32	-0.44
ATELESS			0.31	-0.31	-0.01
RUNOUT				-0.04	0.27
HUNGRY					0.65

Source: Own calculation, 2023

Table 6: Rasch reliability and residuals correlation (*Awash Fentale*)

Rasch reliability					
0.74					
Residual correlation					
	SKIPPED	ATELESS	RUNOUT	HUNGRY	WHOLDAY
FEWFOOD	-0.04	0.07	0.03	0.02	0.01
SKIPPED		-0.01	0.05	0.07	0.05
ATELESS			0.40	-0.34	-0.15
RUNOUT				-0.04	-0.18
HUNGRY					0.13

Source: Own calculation, 2023

Residual correlation

A high residual correlation between a pair of items is considered significant when it exceeds an absolute value of 0.4 (Cafiero et al., 2018). In the context of Rasch modeling, the term "residuals" refers to the differences between observed and expected responses. An essential assumption in Rasch analysis is local independence, indicating that once a person's ability is considered, responses to different items should be independent. The existence of residual correlations among items, even after accounting for individual abilities, may signal a violation of this assumption. When addressing such correlations in Rasch modeling, researchers typically explore potential sources of local dependence, such as item content overlap, response dependencies, or other contextual factors. Modifying the model or excluding problematic items may be necessary to enhance overall model fit. Based on our findings, the residual correlation of all items responses from *Awash Fentale* respondents are within the acceptable range however the values are somehow significant for only items (SKIPPED and HUNGRY) with WHOLDAY) in *Amibara woreda* which may be due to interpretation of those items otherwise the result has no impact on the level of food insecurity of households.

ICC Plot

The Item Characteristic Curves (ICCs) depict the probability of affirmative responses to items plotted against the ability levels to address food insecurity within a household. The ICC plot is a useful tool for understanding how well our items measure the underlying trait (ability to handle food insecurity) and how discriminating each item is across different ability levels. Items positioned on the far right of the plots indicate higher difficulty levels in managing food insecurity, whereas those on the far left suggest lower difficulty levels in dealing with food insecurity situations (Cafiero et al., 2018; Owino et al., 2014) in the districts of *Amibara* and *Awash Fentale*. The x-axis would represent ability levels to handle food insecurity, and the y-axis would represent the probability of items being answered affirmatively.

For example, in *Amibara* district, item 2 (FEWFOODS) is lower levels of difficulty than item 3 (SKIPPED) and both items 2 and 3 are at lower level of difficulty than item 1 (WORRIED) while items 4,5,6,7,8 corresponded to in similar order of higher levels of difficulty in both districts (Figure 3). This imply that households could easily respond to items 2 and 3 than item 1 in regard to food insecurity measurement in *Amibara* while households could easily respond to item 1,2,3 …8 in *Awash Fentale*.

Therefore, households in *Amibara* (highly prosopis invaded sites) are much worried in answering affirmatively against the ability levels to handle the food insecurity situation in their household than *Awash Fentale woreda*.

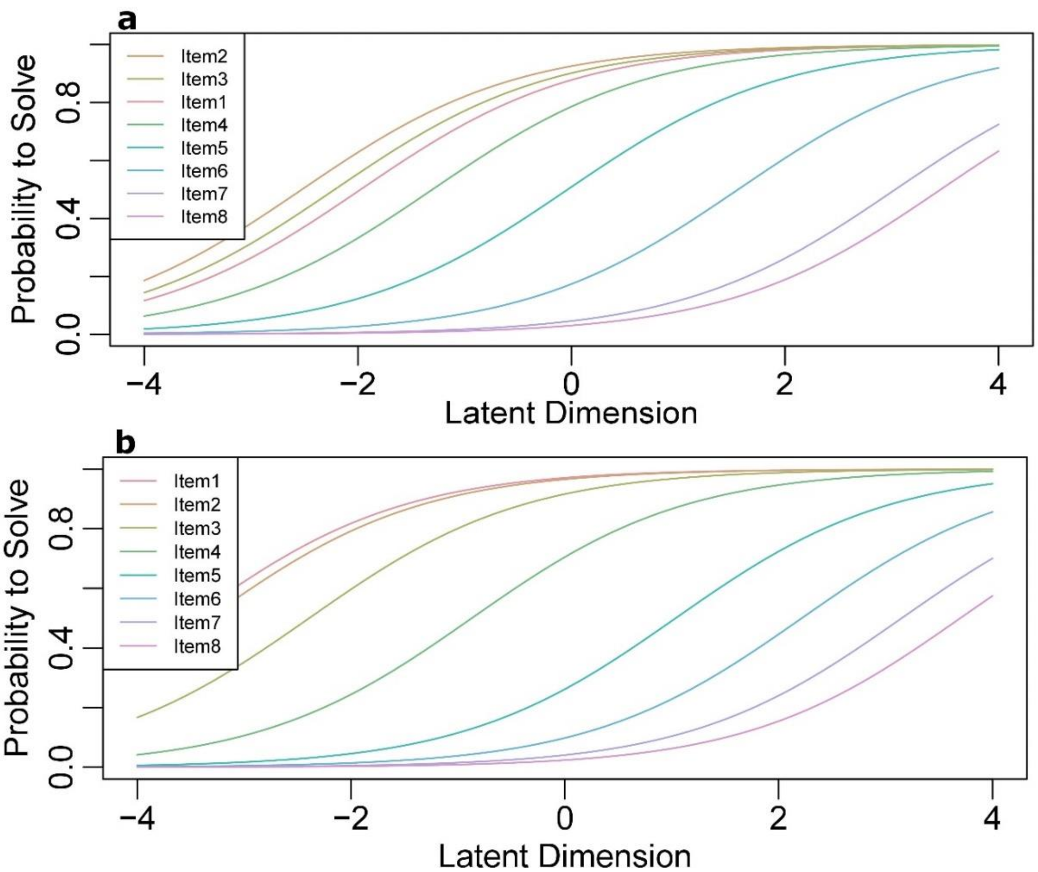


Figure 3: Items characteristic curves for Rasch model check for the districts of *Amibara* (a) and *Awash Fentale* (b)

Equating

Equating becomes a necessary step whenever there is a need to compare measurements between two distinct applications of the Food Insecurity Experience Scale (FIES) or when evaluating results from different locations or countries (Cafiero et al., 2018). This is crucial because the relative positioning of items in terms of severity is contingent upon the specific data collected in each context (Cafiero et al., 2018).

Comparability can be achieved by calibrating the scales on a common metric, in a process called equating. Equating ensures that scores obtained from different forms of the FIES are comparable and can be interpreted on the same underlying scale of food insecurity. It allows for meaningful comparisons and analyses across different versions of the scale, facilitating more robust research and assessment practices (Figure 4). The correlation among the common items is 85.2% and 86.1% and in *Awash Fentale* and *Amibara* districts, respectively (Table 7 and 8). The result showed that SKIPPED is the most discrepant, or different in severity between the two scales.

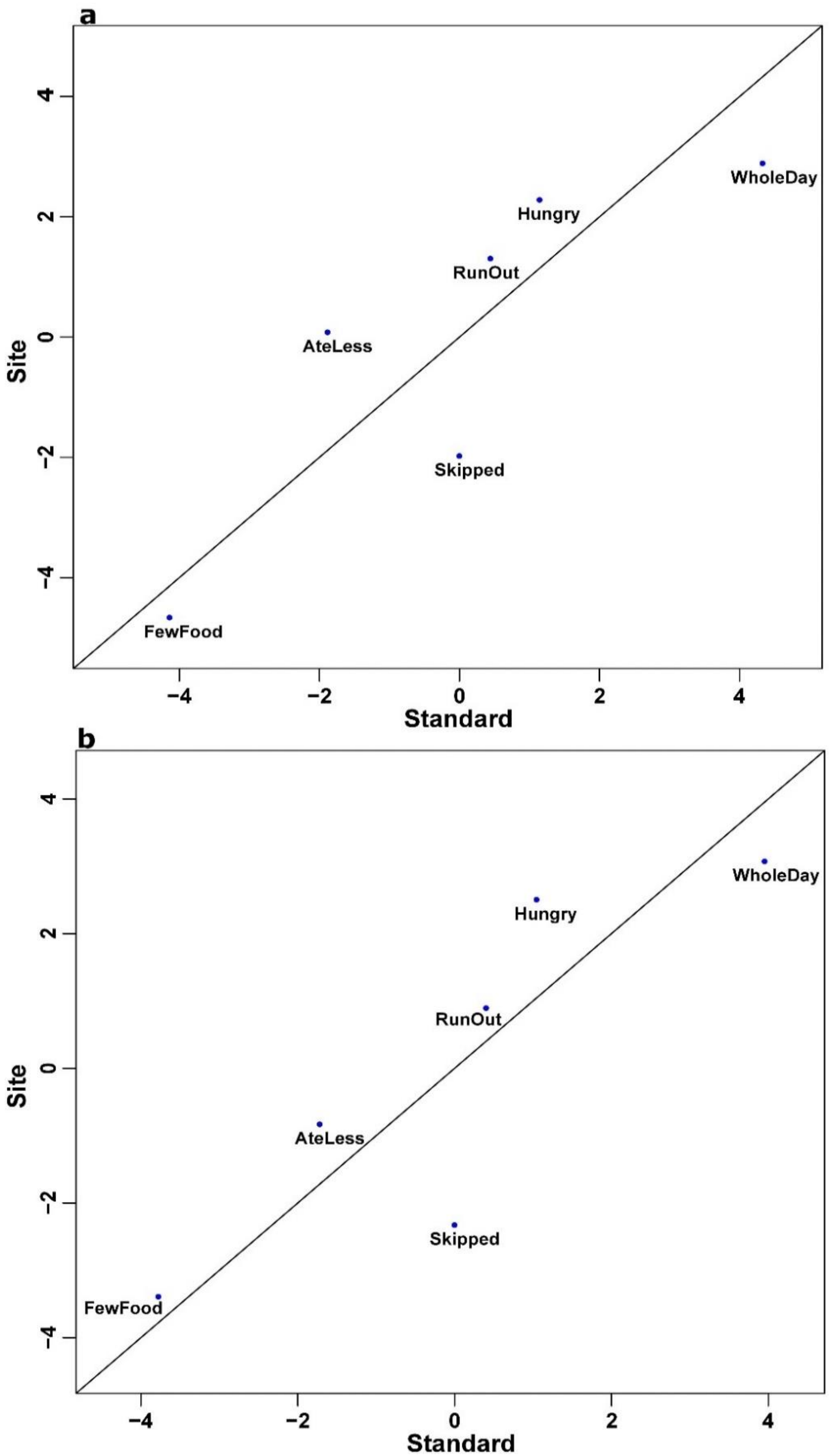


Figure 4: Equating plots a) *Awash Fentale* and b) *Amibara Woredas*

Table 7: Absolute difference in severity of items (*Awash Fentale*)

Fewfood	0.19
Skipped	0.70
AteLess	0.69
RunOut	0.30
Hungry	0.40
WholeDay	0.51
Correlation between common items: ***85.2%***	

Source: Own Survey, 2023

Table 8: Absolute difference in severity of items (*Amibara* district)

Fewfood	0.15
Skipped	0.90
AteLess	0.34
RunOut	0.19
Hungry	0.56
WholeDay	0.34
Correlation between common items: ***86.1%***	

Source: Own Survey, 2023

The prevalence of food insecurity

The findings on the prevalence rates of food insecurity (% of households) revealed a substantial disparity in food security levels between the two districts. At 90% confidence level, the prevalence of food insecurity is significantly high in *Amibara* (Prosopis invaded) *woreda*. The detailed breakdown indicates that in *Amibara*, 94% of households experience moderate food insecurity, and 32% face severe food insecurity. In contrast, in *Awash Fentale*, the corresponding figures are 72% for moderate food insecurity and 21% for severe food insecurity (Table 9).

Table 9: Prevalence of food insecurity by *woreda*

a) *Amibara Woreda*

Moderate or severe	MoE	Severe	MoE
94.23	4.02	32.20	8.02

b) *Awash Fentale Woreda*

Moderate or severe	MoE	Severe	MoE
72.44	9.63	20.81	6.81

Source: Own calculation from Survey, 2023

Thus, the invasion of Prosopis juliflora can have detrimental effects on food security in this affected regions. The shrub competes with native vegetation for water and nutrients, reducing the productivity of grazing lands. Additionally, Prosopis juliflora alters ecosystems, leading to habitat loss and biodiversity decline, raising sustainability issues and further exacerbate food insecurity for local communities dependent on natural resources for their livelihoods.

CONCLUSIONS

The invasion of Prosopis juliflora presents challenges that intersect with sustainable development and food security goals. The spread of this invasive species undermines efforts to achieve environmental sustainability, especially in arid and semi-arid areas of Afar region where the availability and efficient utilization of natural resources is very crucial for the livelihood of the pastoral communities. The significant prevalence of food insecurity in areas invaded by Prosopis Juliflora (*Amibara* district) compared to the non-invaded area (*Awash Fentale*) implies the severity of threat posed by the invasion, highlighting the urgent need for targeted interventions to address the invasion and food insecurity in these communities.

The robustness of the Rasch model with various tests, including infit, outfit, residual correlations, reliability, and item characteristic curves, clearly exhibited the food insecurity status in the area. Notably, the item characteristic curves highlighted the significance of item ordering in gauging household food security. Specifically, it revealed that households in the *Amibara* district (areas invaded by Prosopis Juliflora) expressed higher concerns (WORRIED) about having enough food due to financial constraints compared to households in the *Awash Fentale* district. This suggests that empowering households in *Amibara* with alternative income sources could contribute to mitigating their concerns and enhancing food security. Thus, there need to consider not only the overall level of food security but also the nuanced factors contributing to households' worries and perceived difficulties in ensuring an adequate food supply.

ACKNOWLEDGEMENTS

I would like to express my heartfelt gratitude to my supervisors for their unwavering guidance, encouragement, and invaluable feedback, all of which contributed significantly to the success of this research. Additionally, I extend my thanks to the reviewers and editor of the journal for their constructive feedback and insightful comments, which greatly enhanced the quality of this paper. Furthermore, I am deeply grateful to the communities, elders, and officers of the study areas for their generous contributions, valuable insights, and the wealth of information they shared, which enriched the outcome of this study.

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