



Measuring Household Resilience to Food Insecurity in Rural Northern Ethiopia Using the RIMA and TANGO Approach

Tadsual Asfaw Dessie^{1*}

¹College of Agriculture and Natural Resource, Department of Rural Development and Agricultural Extension, Mekidela Amba University, Tullu Awulia, Ethiopia P.box:32.
ORCID iD: <https://orcid.org/0009-0009-3241-7314>
Email: tadsualasfaw30@gmail.com

*Correspondence: tadsualasfaw30@gmail.com

Data of the Article

First Received: 09 September 2025 | Last Revision Received: 25 October 2025

Accepted: 12 January 2026 | Published Online: 21 January 2026

DOI: <https://doi.org/10.5281/zenodo.20121433>

Keywords

Adaptive Capacity,
Factor Analysis,
Resilience,
Social Safety Nets,
Structural Equation
Modeling.

Measuring household resilience to food insecurity is a growing environmental and socio-economic pressure. This study assessed rural household resilience in rural northern Ethiopia, using two established frameworks: Resilience Index Measurement and Analysis (RIMA) and the Technical Assistance to Non-Governmental Organizations (TANGO) approach. A cross-sectional study design was applied involving 228 households through multi-stage sampling techniques, combined quantitative and qualitative data. Factor analysis and structural equation modeling was used to analyze the data. Based on results from structural equation modeling within the RIMA framework, adaptive capacity (-1.45), assets (-0.66), and social safety nets (-0.99) were negatively associated with resilience, while access to basic services (1.00) contributed positively. In contrast, factor analysis was applied to the TANGO approach data, and the results showed strong positive contributions from absorptive (0.98) and adaptive (0.79) capacities, but a negative loading for transformative capacity (-0.78). Both frameworks produced comparable resilience indices (0.54 for RIMA and 0.51 for TANGO). These findings suggest that policies aimed at strengthening adaptive capacity, improving access to basic services, and reinforcing social protection and institutional support are essential for enhancing rural household resilience to food insecurity.

1. Introduction

1.1. Background of the Study

Food security emerged as a significant issue in the mid-1970s, particularly during the World Food Conference of 1974, which was convened in response to the global food crisis (Clay, 2003). Since then, ensuring food security has remained a central challenge for international, national, and local communities. (FAO, 2020; FAO et al., 2019). Recent estimates indicate that in 2023, approximately 733 million people worldwide faced hunger, with Africa accounting for more than one-third of this figure (FAO et al., 2024). In Sub-Saharan Africa, nearly half of the population experiences varying degrees of food insecurity due to insufficient food production

and recurring shocks (Atara, Tolossa, & Denu, 2019; Liyew & Damtie, 2024; McGuire, 2015).

Ethiopia is among the countries most affected by food insecurity, with both chronic and transitory forms widespread across the population (Beyene et al., 2024; FAO, 2020; Harika et al., 2017; Liyew & Damtie, 2024). Similarly, according to Borku, Utallo, & Tora (2024), Mohamed (2017), Toma et al. (2023), Wubetie et al. (2023) and Yohannes et al. (2023), showed food security situation in Ethiopia is closely connected to the frequent occurrence of food shortages and famine, which is concurrent with repeated drought. Over 41% of the population lives below the poverty line, and more than 31 million people are undernourished (Bezu, 2018; FAO, 2018; Kebede et al., 2016; Telila & Sima, 2024; Welderufael, 2014). Moreover, WFP (2024) reports that

Ethiopia is experiencing one of its worst food crises, with an estimated 15.8 million people in need of assistance. The Amhara Region, particularly North Wollo Zone, is highly vulnerable, with agricultural production lasting only nine months and recurrent droughts exacerbating food shortages (Aragie & Genanu, 2017; Goshu, 2016; Kasie et al., 2017; Negash, 2019; Wassie et al., 2023).

In response, resilience has gained increasing attention as a framework for addressing poverty, vulnerability, and food crises (FAO, 2016; Frankenberger & Smith, 2015; Knippenberg, Jensen, & Conostas, 2019; Smith & Frankenberger, 2018). Conostas & Barrett (2013) argue that the rapid adoption of resilience reflects its value as a guiding principle in designing responses to food insecurity. In agriculture, resilience refers to households' capacity to absorb shocks, adapt to stresses, and recover in ways that sustain or improve food security (Alinovi et al., 2010a; FAO, 2014). It serves both as an analytical tool and a policy framework for understanding how rural households maintain well-being under stress.

Although several studies have assessed household resilience in Ethiopia using frameworks such as RIMA and TANGO (Demeke & Tefera, 2013; Maxwell et al., 2013; Negussie, 2010; Tefera, 2014; Tefera & Kayitakire, 2014; Vaitla et al., 2012), limitations remain. Common gaps include inconsistent measurement dimensions, insufficient justification for indicator selection, limited integration of multiple indicators, and underutilization of robust analytical models. More recent studies, Guyu & Muluneh (2015), Frankenberger & Smith (2015), (Kebede et al., 2016), Kasie et al. (2017), Atara, Tolossa, & Denu (2020), and Beyene et al. (2023) investigated resilience across different regions, focusing on seasonal food insecurity, shocks, livelihood outcomes, and multiple resilience dimensions. Later, the results of earlier studies conducted on resilience vary within and across countries due to differences in socioeconomic characteristics, institutional factors, and population dynamics, methodological gap (RIMA and TANGO measurement analyses) and agro-ecological conditions.

Based on the preceding discussion, several gaps in the literature on household resilience to food insecurity in Ethiopia can be identified. First, most previous studies employed different and inconsistent dimensions to measure resilience, despite the Food and Agricultural Organization (FAO) having developed standardized resilience dimensions. Second, earlier research often relied on inappropriate or limited analytical models, restricting the robustness of resilience assessments. To address

this, the study applies factor analysis and structural equation modeling to investigate household resilience comprehensively. Third, resilience is context-specific and must be examined within a particular geographical setting (Constas, Frankenberger, & Hoddinott, 2014), yet many studies have not fully accounted for local variations. Furthermore, although both RIMA and TANGO methods are widely applied, no study has compared their results using the same dataset (Villoslada, 2019). Building on these gaps, this study investigates household resilience to food insecurity in rural northern Ethiopia by jointly applying RIMA and TANGO frameworks, using factor analysis and structural equation modeling to provide a comprehensive assessment.

2. Methods

2.1. The Study Area

The study was conducted in northern part of Ethiopia particularly Mekiet district, North Wollo zone, and it bordered to the South by the Dawunt and Wadila districts, to the West by the Lay Gayint district of the South Gondar zone, to the North by the Lasta and Bugna districts, and to the East by the Gazo district (Siyum, Giziew, & Abebe, 2022). As shown in Figure 1, the location of the district is located between 11°35'50" N - 12°20'30" N north latitudes, and 38°32'35" E - 39°16'40" E east longitudes. The agro-ecological zones of the study area are lowlands (27%), midlands (63%), and highlands. The estimated average annual rainfall varies from 600 mm in the lowlands, 900 mm in the midlands and 1120 mm in the highlands, while the region's typical highest and lowest temperatures are roughly 24.6°C and 12.1°C, respectively. The local dwellers relies primarily on small-scale rain agriculture for their livelihood (MWADO, 2024).

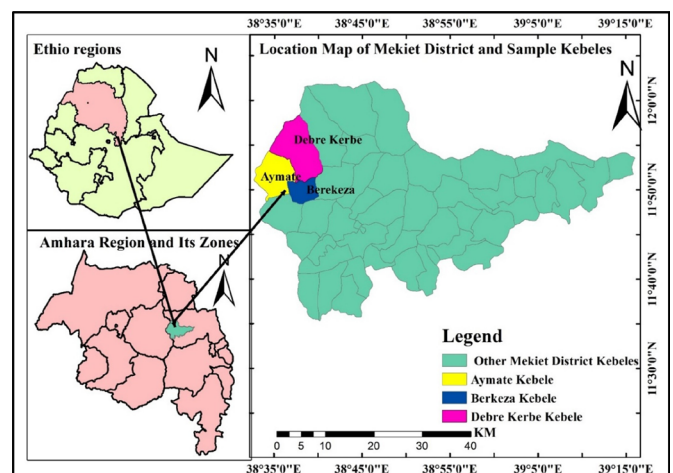


Figure 1: Location map of the study area.
Source: Own extraction from Ethiopian map shape file, 2018.

2.2. Research Design and Sampling Procedure

The study employed a cross-sectional research design, collecting data from households at a single point in time. A household survey was the primary research strategy, using a quantitative approach complemented by qualitative methods. A multistage sampling technique was applied to select the study area and sample households. Firstly, Mekiet district was purposively chosen due to its chronic food insecurity, high exposure to drought, and vulnerability of its population. Secondly, the district was stratified into three agro-ecological zones, highland, midland, and lowland but only midland and lowland kebeles were included, as they host most of the population (63% midland, 27% lowland), experience frequent droughts, high food insecurity, and limited access to basic services (MWADO, 2024). Thirdly, proportional sampling ensured fair representation across the selected agro-ecological zones. Three kebeles were included: Berekeza and Aymate (midland) and Debrekerbie (lowland). The minimum sample size was calculated using Cochran (1977) formula for large populations with a 95% confidence level, 5% margin of error, and an estimated population proportion 0.1, resulting in 138 households. The total number of rural households in the selected kebeles was approximately 4,520, which served as the target population (N) for the study. Since the calculated sample size represented less than 5% of the total population ($n/N \leq 0.05$), the finite population correction (FPC) was not applied. The formula used was as follows:

$$n = \frac{z^2 \times pq}{d^2} \quad n = \frac{1.96^2 \times 0.1 \times (1-0.1)}{(0.05)^2} = 138$$

Considering a 10% non-response rate and a design effect of 1.5 due to multistage sampling, the final sample size was increased to 228 households. (Naing, Winn, & Rusli, 2006). The final adjusted sample size was calculated as:

$$n_{final} = (138 + 10\%) \times 1.5 = 228$$

The total sample size was then allocated to each selected kebele using probability proportional to size (PPS) based on the number of households in each kebele. Finally, within each kebele, households were selected using systematic random sampling from the household lists obtained from kebele administrative records. The sampling interval (k) was determined by dividing the total number of households in each kebele by the allocated sample size, and the first household was selected randomly to begin the sampling process.

2.3. Methods of Data Sources and Collection

This study used both primary and secondary data. Primary data were collected from rural households, the unit of analysis, using structured interviews, key informant interviews, and focus group discussions. In total, nine key informants and three focus group discussions were conducted in each kebele to enhance validity and provide a comprehensive understanding of household resilience to food insecurity. Secondary data were obtained from offices at kebele to zonal levels, including agriculture, trade and industry, and risk and disaster management. These sources provided information on household numbers, infrastructure, access to social services, food security status, and support programs such as social safety nets and emergency aid.

2.4. Method of Data Analysis

2.4.1. Resilience Index Measurement and Analysis Model

The study is grounded in FAO’s Resilience Index Measurement and Analysis (RIMA) model, which constructs resilience as a latent variable in line with prior applications and recent literature (Alinovi et al., 2010a; Alinovi, Mane, & Romano, 2010b; FAO, 2016). The FAO (2016) method, most relevant the study area, identifies four key resilience pillars; access to basic services (ABS), adaptive capacity (AC), Assets (AST), and social safety nets (SSN).

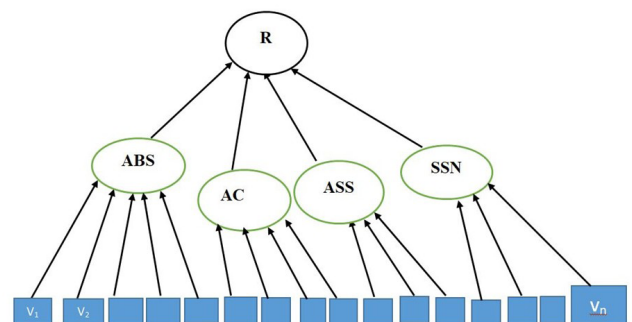


Figure 2: A Path Diagram of Household’s Resilience Estimation Procedure.

Source: Adopted from FAO (2016)

The overall household resilience capacity and its RIMA dimensions were estimated in a two-step procedure by using factor analysis (FA) and structural equation modeling (SEM). In the first stage, FA was applied to reduce observable indicators into latent variables, known

as resilience pillars, by assigning appropriate weights to each indicator (Bollen, 2002; Demeke & Tefera, 2013). This approach assumes that one or more latent variables underlie the observed indicators, expressed as:

$$Y_i = \lambda_0 + \lambda_1 \varepsilon_{i,1} + \lambda_2 \varepsilon_{i,2} + \dots + \lambda_k \varepsilon_{i,k} + \mu_i$$

Where; Y_i = observed indicator for the i^{th} case, λ_0 = intercept term, $\varepsilon_{i,1} \dots \varepsilon_{i,k}$ = factor loading for the 1st through k case, μ_i = unique variable or error term.

The validity of FA was tested using Kaiser-Meyer-Olkin (KMO) sampling adequacy, Bartlett’s test of sphericity, checks for multicollinearity, and factor loadings (DiStefano, Zhu, & Mindrila, 2009; Field, 2009; Kaiser, 1960; Odum, 2011; Yong & Pearce, 2013). The Kaiser–Meyer–Olkin (KMO) test measures sampling adequacy and indicates whether the variables share sufficient common variance to justify the application of factor analysis; values closer to 1 suggest that factor analysis is appropriate. Bartlett’s test of sphericity examines whether the correlation matrix significantly differs from an identity matrix, meaning that the variables are sufficiently correlated to allow meaningful factor extraction. A statistically significant result ($p < 0.05$) indicates that factor analysis is suitable for the dataset.

In the second step, Structural Equation Modeling (SEM) was used to estimate the latent household resilience capacity index (RCI) based on the four dimensions identified earlier (Schumacker & Lomax, 2004). SEM offers key advantages: it captures both direct and indirect effects between variables, allows multiple indicators to explain a latent construct, and incorporates measurement error, thereby improving model accuracy (Acock, 2013; Bollen & Hoyle, 2012; Wuensch, 2016). Although more computationally demanding than factor analysis, SEM enables model calibration to achieve satisfactory goodness of fit (Bollen et al., 2007).

As with factor analysis, the appropriateness of SEM was evaluated using standard goodness-of-fit indices, including Chi-square, AIC, BIC, R^2 , RMSEA, CFI, TLI, and SRMR (Huber, 2014). These fit indices assess how well the proposed model represents the observed data. For example, RMSEA and SRMR measure the discrepancy between the observed and model-implied covariance matrices, while CFI and TLI compare the proposed model with a baseline model to evaluate improvement in fit. Lower RMSEA and SRMR values and higher CFI and TLI values indicate better model fit. A sample size of 200–500 is generally recommended

for SEM (Çelik & Yılmaz, 2013). Table 1 summarizes the acceptable thresholds for these indices.

Table 1: Goodness of Fit Values of SEM.

Fit Indices	Goodness of Fit Values
X^2	p-value > 0.05
R^2	Values closer to 1 indicate good fit
RMSEA	$0 < RMSEA < 0,05$
AIC	Smaller (in absolute value) is better
BIC	Smaller (in absolute value) is better
CFI	$0,97 < CFI < 1$
TLI	$TLI > 0.95$
SRMR	$SRMR < 0.08$

Source: (Huber, 2014, Bayram, 2013)

Using SEM, the four resilience dimensions, access to basic services (ABS), adaptive capacity (AC), assets (AST), and social safety nets (SSN) were combined to construct the household Resilience Capacity Index (RCI), expressed as:

$$RCI_{i,t} = f(ABS_{i,t}AC_{i,t}AST_{i,t}SSN_{i,t}) + \varepsilon_{i,t}$$

2.4.2. Technical assistance to non-governmental organization (TANGO) Resilience Measurement and Analysis Approach

The second widely applied method for assessing household resilience to food insecurity is the TANGO approach. Originally developed for program evaluation in Ethiopia (Frankenberger & Smith, 2015) and later applied in Bangladesh (Smith & Frankenberger, 2018), it has since become a recommended framework for resilience analysis (Henly-Shepard & Sagara, 2018). The TANGO model emphasizes household- and community-level capacities, focusing on three latent variables, absorptive, adaptive, and transformative, which collectively enhance resilience. These dimensions are estimated using observable household-level indicators.

Similar to the RIMA framework, TANGO follows a two-step procedure (Smith & Frankenberger, 2018; Upton, Constenla-Villoslada, & Barrett, 2022). First, indices for the three capacities are derived through factor analysis. Second, these indices are combined to construct the overall Resilience Capacity Index (RCI) using the following expression:

$$RCI_i = (\beta_1 ABC_i + \beta_2 ADC_i + \beta_3 TC_i)$$

Where: RCI_i denotes resilience capacity index, ABC_i absorptive capacity, ADC_i adaptive capacity, TC_i Transformative capacity. The coefficients β_n are factor loadings estimated from inter-correlations among the three capacity indexes. To facilitate interpretation, a

min-max rescaling is applied, converting values to a 0–100 scale. Accordingly, households with scores closer to 0 are less resilient, while those near 100 are highly resilient (Lascano Galarza, 2020).

$$\text{Factor Index (0 – 100)} = \frac{\text{Factor Index} - \text{Min}}{\text{Max} - \text{Min}}$$

The robustness of the factor analysis was verified through standard statistical diagnostics, including the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy, Bartlett’s test of sphericity, assessment of multicollinearity or singularity, and factor loadings (DiStefano et al., 2009; Field, 2009; Kaiser, 1960; Odum, 2011; Yong & Pearce, 2013).

After measuring household resilience using the RIMA and TANGO approach, we determined how those two empirical identifications of resilience relate to each other. Moreover, data gain from focus group discussions and key informant interviews were analyzed concurrently and thematically with quantitative results.

2.5. Definition and Hypothesis of Variables

The study was operationalized by a priori specifying the relationship between the non-observed resilience pillars with the relevant indicators based on theoretical and empirical evidence from the resilience studies as shown in Table 2.

Table 2: Observed Variables and Expected Sign on Resilience.

Pillars	Variable Code	Variable Description	Expected Effect on Resilience
ABS	credit (1=yes)	Percentage of households who have access to credit services in their <i>kebele</i> (%)	+
	helth (1=yes)	Percentage of households who have access to health services in their <i>kebele</i> (%)	+
	Markt (1=yes)	Percentage of households who have access to market access in their <i>kebele</i> (%)	+
	Exten (1=yes)	Percentage of households who have access to extension services in their <i>kebele</i> (%)	+
	Town	Households’ residence distance from district town center in kilometers	-
AC	Income	Income diversification index ¹	+
	Lives	Livestock diversification index ²	+
	Crop	Crop diversification index ³	+
	ltrcy (1=yes)	Ability to read and write	+
AST	Agrsi	Agricultural asset index ⁴	+
	Nonagri	Non-agricultural asset index ⁵	
	Land	Size of agricultural land measured in hectare per capita	+
	TLU	Livestock number in tropical livestock unit per capita ⁶	+
SSN	tranf	Cash transfers per capita from formal source	+
	trani	cash transfers per capita from informal sources	+

Source: (FAO, 2016, Alinovi et al., 2010)

¹Income diversification index is created through factor analysis. A list of variables assumes value 1 or 0 is used, depending on whether a household has been involved in farming activity; employment activities; self-employment activities; received transfers and earned income from rent.

²Livestock diversification is also created through factor analysis. A list of variables assumes value 1 or 0 is used, depending on whether a household has been involved in rearing cattle, shoats, donkey/mule/horse, and camels.

³Crop diversification is created through factor analysis. A list of variables assumes value 1 or 0 is used, depending on whether a household has been involved in planting wheat, barely, beans, sorghum, teff, and lentil in their agricultural field in the past cropping season.

⁴Agricultural asset index is created through factor analysis. A list of variables assumes value 1 or 0 is used, depends on whether a household has specific productive plough, sickle, pickaxe, axe, and spade.

⁵Non-agricultural asset index created through factor analysis. A list of variables assumes value 1 or 0 is used, depending on whether a household has specific non-productive assets, mobile telephone, radio/television, jewelry (gold, silver), and bed (wooden or metal).

⁶TLU standardizes different types of livestock into a single unit of measurement. The conversion factor adopted is 0.7 cattle; 0.6 donkeys /horses; 0.1 sheep and goat; 0.01 poultry (Tibebu et al. 2018).

Table 3 shows the observed variables of resilience dimension in TANGO approach (Smith & Frankenberger,

2018) that are used in resilience analysis with their expected relationships.

Table 3: Explanatory Variables of TANGO Dimensions and their Expected Effects.

Resilience Capacity Dimensions	Variable Description	Expected Effect on Resilience
Absorptive Capacity	Bonding Social Capital index	+
	Asset Ownership index ¹	+
	Cash Savings (yes=1)	-
	Access to informal safety nets (yes=1)	+
	Disaster preparedness and mitigation index ²	-
Adaptive Capacity	Bridging Social Capital index	+
	Linking Social Capital (yes=1)	+
	Livelihood Diversity index	+
	Human Capital index ³	+
	Access to Information index ⁴	+

Resilience Capacity Dimensions	Variable Description	Expected Effect on Resilience
Transformative Capacity	Quality of Governance (yes=1)	+
	Access to markets (yes=1)	+
	Access to public services index ⁵	+
	Access to formal safety nets (yes)	+
	Access to communal natural resources ⁶ index	+
	Access to extension services (yes =1)	+

Note: + = positive relationship; - = negative relationship.

Source: Smith and Franken Berger, 2018; 2021

¹Asset ownership is created through factor analysis; a list of variables assumes a value of 1 or 0, depending on, TLU, land size, agricultural and durable asset index.

²Disaster preparedness and mitigation is created through factor analysis, a list of variables assumes a value of 1 or 0, including, improved infrastructure to mitigate shock, disaster early warning system, local coping mechanisms, political instability and DRR awareness in kebeles.

³Human capital is created through factor analysis, a list of variables assumes a value of 1 or 0, including ability to read and write, adults have a primary or higher education, and job or training.

⁴Access to information is created through factor analysis a list of variables assuming a value of 1 and 0, including's early warning for natural hazards, water price, animal health, crop health, improved crop production, improved livestock production, market price, opportunity for borrowing.

⁵Access to public services is created through factor analysis a list of variables assuming a value of 1 and 0, including's, availability of primary schools, road transport, health services, police security, piped water, and electricity.

⁶Access to communal resource is created by factor analysis, a list of variables assuming 1 and 0, includes, communal grazing land, water source for livestock, and source of irrigation water.

3. Results and Discussions

3.1. Measuring Household Resilience to Food Insecurity Using RIMA Approach

In the RIMA approach, resilience capacity is measured through four dimensions: Access to Basic Services (ABS), Assets (AST), Social Safety Nets (SSN), and Adaptive Capacity (AC). Factor analysis is first applied to estimate each dimension from observed variables, and then Structural Equation Modeling (SEM) is used to predict the household resilience capacity index (RCI). Factor analysis identifies common factors from observed data, calculating factor loadings that help determine which factors represent the resilience dimensions. Thus, each pillar of resilience, namely adaptive capacity, asset, access to basic services, and social safety net are estimated distinctly as follows.

3.2. Access to Basic Services

Access to Basic Services (ABS) is a key resilience dimension in the RIMA approach, as it strengthens household capacity to cope with and recover from shocks (Alinovi et al., 2010a; FAO, 2016). To estimate ABS, the study analyzed household access to credit, health services, markets, extension services, and distance to the nearest district town.

The factor analysis retained three factors with Eigenvalues¹ ≥1; explaining 74.65% of the total variance (see Appendix Table 1). As can presented in Table 4, the model's validity was confirmed through

1. Eigenvalues represent the amount of variance explained by each factor. Higher eigenvalues indicate factors that explain more of the variance in the data. Lower eigenvalues suggest that the factor explains less variance and may be less important. In factor analysis, an eigenvalue greater than 1 is often used as a rule of thumb to determine whether a factor is significant or should be retained in the analysis. Factors with eigenvalues less than 1 are typically considered less significant.

Bartlett's Test of Sphericity (Chi-square = 269.348, p=0.000) and the Kaiser-Meyer-Olkin measure (KMO = 0.53), both indicating an appropriate model. Factor 1 was mainly explained by market access, Factor 2 was explained by access to extension services, health services, and proximity to the district town, and Factor 3 was explained by access to credit. All factor loadings exceeded the minimum threshold of 0.364 (Field, 2009), confirming statistical significance. Similar findings by d'Errico, Romano, & Pietrelli (2018) and Ado, Savadogo, & Abdoul-Azize (2019) emphasize the importance of markets, credit, and infrastructure (health and roads) in shaping household resilience. Qualitative results supported these findings. FGD participants stressed that food insecurity is closely tied to limited access to markets, extension, health care, and credit. They noted that long distances to markets restrict farmers' ability to buy and sell produce, while poor road networks further limit opportunities. A key informant from Debrekerbie kebele added that, even when credit is available, lack of market access and infrastructure prevents households from earning sustainable income.

Thus, the ABS index for each household was computed using weighted factor scores, aggregated according to their explained variance:

$$ABS = \frac{0.33 * factor\ 1 + 0.215 * factor\ 2 + 0.199 * factor\ 3}{3}$$

The result obtained from this equation is further used to estimate resilience capacity index.



Table 4: Factor Loadings of Access to basic Services.

Variables	Factor 1	Factor 2	Factor 3	Uniqueness
Access to credit	0.5592	-0.0002	0.6729	0.2345
Access to market	0.8820	-0.1845	-0.1121	0.1754
Access to extension service	0.2178	0.7723	0.0963	0.3468
Access to health service	0.2546	0.4224	-0.7796	0.1491
Distance to nearest district town	0.0994	0.6671	0.3059	0.4515
Bartlett Test of Sphericity: Chi-square = 269.348, df = (15), p=0.000				
Kaiser-Meyer-Olkin Measure of Sampling Adequacy = .530				
Determinant of R-matrix = 0.301				
Source: Author's computation using household survey data (2025)				

3.3. Adaptive Capacity

Adaptive capacity is a key factor in determining household resilience, referring to the ability to adjust and respond to environmental changes. It is measured using four observed variables: the income diversification index, livestock diversification index, crop diversification index, and the literacy status of the household head. These variables were estimated through factor analysis.

The factor loadings for income, crop, and livestock diversification indices were statistically significant, with values above 0.364, meeting the necessary criteria for a good factor analysis model. As presented in Table 5, statistical checks, including Bartlett's Test of Sphericity (Chi-square = 26.472, p = 0.000) and the Kaiser-Meyer-Olkin test (KMO = 0.556), confirmed model adequacy. Additionally, two factors were retained since their eigenvalue is greater than one as recommended by

Kaiser Rule and those factors explain 60.56% of the total variation (see Appendix Table 2).

Moreover, all variables have strong loadings on the first factor, except the livestock diversification index, which contributed to the second factor. Likewise, studies by d'Errico et al. (2018) and Beyene et al. (2023) reported that, the importance of education and income diversification in adaptive capacity. These factors positively impact household resilience to food insecurity. The adaptive capacity was estimated using a weighted sum method, combining the factor scores based on their variance contribution. Finally, adaptive capacity was estimated as follows.

$$AC = \frac{0.349 * factor\ 1 + 0.256 * factor\ 2}{2}$$

The result obtained from this equation is further used to estimate resilience capacity index.

Table 5: Factor Loadings of Adaptive Capacity.

Variables	Factor 1	Factor 2	Uniqueness
Income diversification index	0.6726	0.3077	0.4529
Crop diversification index	0.5950	-0.4029	0.4836
Livestock diversification index	0.5021	0.6907	0.2708
Literacy rate	0.5805	-0.5411	0.3703
Bartlett Test of Sphericity: (Chi-square = 26.472, df = (6), p=0.000).			
Kaiser-Meyer-Olkin Measure of Sampling Adequacy = .556			
Determinant of R-matrix = 0.889			
Source: Author's computation using household survey data (2025)			

3.4. Asset

The Asset (AST) is key unobservable factors within the resilience capacity index, representing both financial and non-financial resources that help households sustain their livelihoods. It is measured through four observed variables: per capita agricultural land (in hectares), quantity of livestock (measured in tropical livestock units, TLU), the agricultural asset index, and the non-agricultural asset index. The agricultural and non-agricultural asset indices were calculated using factor analysis to approximate the Asset (AST) index. The statistical requirements for a reliable FA model

were assessed as indicated in Table 6. Bartlett's Test of Sphericity yielded significant results (Chi-square = 24.624, df = 6, p = 0.000). The KMO Measure of Sampling Adequacy was 0.514, which exceeds the minimal requirement of 0.5. Additionally, the determinant of the R-matrix (0.896) also surpasses the specified level.

All four variables contributed significantly to the Asset latent variable, with factor loadings above the threshold of 0.364. Previous studies, such as those by Guyu & Muluneh (2015) and d'Errico et al. (2018), confirmed that land, livestock, and both agricultural

and non-agricultural assets play vital roles in household resilience. Similarly, Ado et al. (2019) highlighted the strong correlation between TLU, farm size, and the non-agricultural asset index with the Asset latent variable, emphasizing their importance in strengthening resilience to food insecurity.

Table 6: Factor Loadings of Asset Index.

Variables	Factor 1	Factor 2	Uniqueness
Nonagricultural asset index	0.1428	0.8756	0.2130
Agricultural asset index	0.6161	-0.4323	0.4336
land size	0.7905	-0.0059	0.3750
TLU	0.5689	0.2565	0.6105
Bartlett test of sphericity: (Chi-square = 24.624, df = 6, p-value = 0.000)			
KMO Measure of Sampling Adequacy = .514			
Determinant of the R- matrix = 0.896			
Source: Author's computation using household survey data (2025)			

On the estimations of asset index, two factors were extracted since their eigenvalue is greater than one as recommended by Kaiser Rule and those factors explain 59.19% of the total variation (see Appendix Table 3). Therefore, the combined factor score of two factors is used to estimate the latent variable AST. The weighted sum method is thus used to estimate the AST by multiplying each factor score by its own proportion of variance. As a result, they were used to estimate AST as follows:

$$AST = \frac{0.337 * factor\ 1 + 0.254 * factor\ 2}{2}$$

The value gained from this equation is further used to estimate resilience capacity index (RCI).

3.5. Social safety net

Social Safety Nets (SSN) capture household reliance on formal and informal assistance during shocks, such as cash or in-kind transfers (Alinovi et al., 2010a). Since only two observed variables were available, principal component analysis (PCA) was applied instead of factor analysis (Tabachnick & Fidell, 2007).

The PCA model was valid, with Bartlett's Test significant ($\chi^2 = 30.548$, $p = 0.000$), KMO = 0.500, and R-matrix determinant = 0.873. One factor with an Eigenvalue ≥ 1 explained 67.8% of the variation (see Appendix Table 4). Both formal and informal transfers showed strong positive correlations with SSN (0.9117 and 0.7084, respectively). Supporting studies d'Errico et al. (2018) and Ciani & Romano (2014) confirm the role of transfers in strengthening resilience. FGD participants highlighted that programs like the PSNP and emergency aid help reduce poverty and food insecurity, though

mainly as short-term solutions rather than drivers of lasting household improvement.

Table 7: Correlations of Social Safety Nets with Variables.

Variables	Corr. SSN index
SSN index	1.0000
Cash transfers from formal sources	0.9117
Cash transfers from informal sources	0.7084
Source: Author's computation using household survey data (2025)	

3.6. Aggregating Household Resilience Capacity in RIMA approach using SEM

After estimating resilience dimensions through factor analysis, Structural Equation Modeling (SEM) was applied to assess their significance and construct the overall Resilience Capacity Index (RCI). As presented in Table 8, the model satisfied statistical and goodness-of-fit requirements ($\chi^2 (2) = 4.6$, RMSEA = 0.075, CFI = 0.971, TLI = 0.913, SRMR = 0.029), confirming its validity (See Appendix Table 5).

Table 8: SEM Results of Resilience Capacity in RIMA Method.

Resilience Capacity Dimensions	Values
ABS	1*** (constrained)
AC	-1.45*** (0.05)
AST	-.66*** (0.05)
SSN	-.99*** (0.02)
Chi2(2)	4.6
p-value	0.000
RMSEA	0.075
p-value_RMSEA	0.05
AIC	12.21
BIC	53.36
CFI	0.971
TLI	0.913
SRMR	0.029
Note: (1) Standard errors in parentheses; (2) *** p<0.01, ** p<0.05, * p<0.1 indicate 1%, 5%.and 10 % level of significance respectively.	

SEM results showed that Access to Basic Services (ABS), constrained to 1, served as the reference dimension. Adaptive Capacity (AC, -1.45***), Assets (AST, -0.66***), and Social Safety Nets (SSN, -0.99***) all had significant negative effects on resilience ($p < 0.01$). This implies that increases in these dimensions, under current conditions, reflect heightened vulnerability and worsening food insecurity, consistent with findings from Kebede et al. (2016). Among them, AC had the strongest negative effect, highlighting its central role in shaping resilience. Similar results were reported (d'Errico et al., 2018) in Tanzania and Uganda. Qualitative findings further explained this outcome. Focus group discussions revealed households' limited adaptive capacity, with heavy reliance on rain-fed farming, weak crop and livestock diversification, and scarce off-farm activities. Low literacy and poor access

to technical training, agricultural inputs, and extension services were also identified as major barriers. Key informants emphasized that these constraints hinder innovation, income diversification, and sustainable resource use. Together, these results confirm that weak adaptive capacity is a major driver of household vulnerability to food insecurity in the study area.

3.7. Relationship between RIMA Dimensions and the Resilience Capacity Index

A two-way scatter plot was used to examine the relationships between the four latent variables of the RIMA approach and the Resilience Capacity Index (RCI). The line of best fit illustrates the strength and direction of correlations, with points closer to the line indicating stronger relationships. In theory, increases in these latent

variables should enhance household resilience to food insecurity (FAO, 2016; Kasie et al., 2017).

As shown in Figure 3, Access to Basic Services (ABS) displayed a positive association with the RCI, whereas Adaptive Capacity (AC), Assets (AST), and Social Safety Nets (SSN) showed negative relationships. Notably, even at higher resilience levels, AC, AST, and SSN continued to decline. This counterintuitive pattern likely reflects the context of the study area, a chronically food-insecure district where households diversify livelihoods primarily as a coping mechanism rather than as a pathway to resilience (Aragie & Genanu, 2017; Goshu, 2016). Similar findings in Ethiopia highlight that livelihood diversification often functions as a survival response to shocks rather than a sign of resilience (Berhanu, Colman, & Fayissa, 2007; Carter et al., 2006; Kasie et al., 2017; Vaitla et al., 2012).

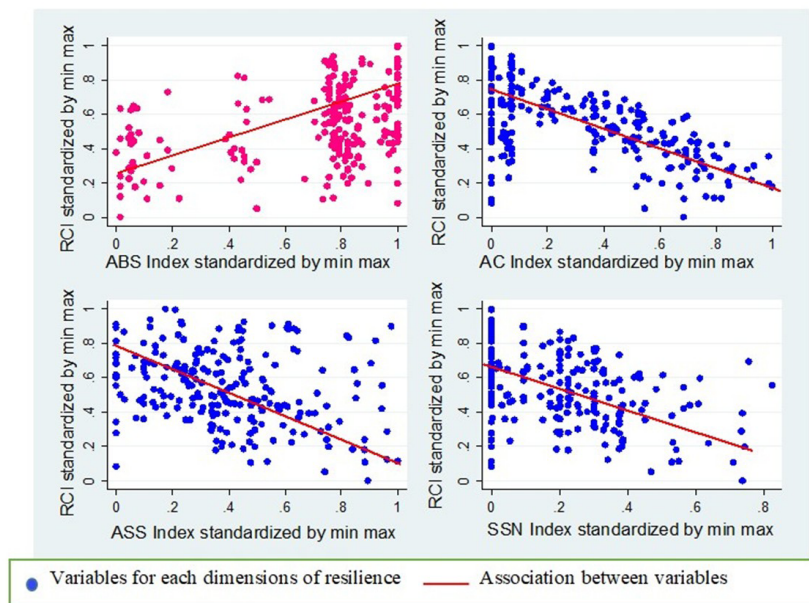


Figure 3: Scatter Plots for Resilience Capacity to Food Insecurity with RIMA Dimensions.

In summary, SEM and scatter plot results indicate that household resilience is most strongly shaped by adaptive capacity, encompassing income, crop, and livestock diversification as well as literacy. Households with higher adaptive capacity are more resilient to agricultural drought, consistent with earlier studies (Gambo Boukary, Diaw, & Wünscher, 2016). These findings suggest that resilience-focused interventions should prioritize strengthening adaptive capacity alongside basic services to effectively reduce vulnerability to food insecurity.

3.8. Measuring Household Resilience to Food Insecurity Using the TANGO Approach

The TANGO approach assesses resilience through three

dimensions: absorptive, adaptive, and transformative capacities. These dimensions were estimated using factor analysis (FA) on observable variables, with the resulting latent variables contributing to the overall household Resilience Capacity Index (RCI).

3.9. Absorptive Capacity

Absorptive capacity reflects households' ability to reduce exposure to shocks and recover quickly, thereby safeguarding long-term food security. It was measured using five observed variables: bonding social capital, asset ownership, cash savings, access to informal safety nets, and disaster preparedness. Prior to estimation, variables were indexed and analyzed through factor analysis.

Two factors were retained, explaining 55% of the total variation (34% and 21%) (See Appendix Table 6). (KMO = 0.593; Bartlett’s $\chi^2(10) = 81.05, p < 0.001$). All five variables loaded significantly (> 0.364), with access to informal safety nets and bonding social capital showing strong

positive contributions. Conversely, asset ownership and disaster preparedness had lower or negative loadings, indicating weaker influence. These findings echo evidence from Uganda, where informal safety nets strongly shaped absorptive capacity (Sunday et al., 2023).

Table 9: Factor Loadings of Absorptive Capacity.

Variables	Factor1	Factor2	Uniqueness
Bonding Social Capital Index	0.7997	-0.0519	0.3578
Asset ownership index	-0.5959	-0.0797	0.6386
Cash saving	0.0196	0.8162	0.3334
Access to informal safety nets	0.7393	0.2703	0.3803
Disaster preparedness and mitigation index	0.3972	-0.5583	0.5305
Determinant of the correlation matrix = 0.697			
Bartlett test of sphericity, Chi-square = 81.05, Df =10, p-value = 0.000			
Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO =0.593)			
Source: Author’s computation using household survey data (2025)			

Given their contributions, the two retained factors were combined to estimate absorptive capacity as:

$$ABC = \frac{0.34 * \text{factor1} + 0.21 * \text{factor2}}{2}$$

This index was subsequently incorporated into the estimation of household resilience capacity under the TANGO approach.

3.10. Adaptive Capacity

Adaptive capacity in the TANGO approach reflects households’ ability to make informed livelihood choices in response to shocks. It was measured using five variables: bridging social capital, linking social capital, livelihood diversity, human capital, and access to information. Prior to estimation, these variables were indexed and analyzed through factor analysis.

Two components were retained; satisfying Kaiser’s rule and jointly explaining a significant share of variance (see Appendix Table 7). All variables loaded significantly (> 0.364), though with varying contributions. Linking social capital and access to information had the strongest positive loadings, confirming their importance in resilience building. In contrast, the human capital index had negative loadings, suggesting that low literacy levels reduce households’ ability to adapt. These findings are consistent with Sunday et al. (2023) and Atara et al. (2020), who highlight the role of social networks and information access in strengthening resilience to food insecurity.

The retained components were combined using the Bartlett scoring method, weighted by their explained variance, to estimate the Adaptive Capacity (AC) index as:

$$AC = \frac{0.293 * \text{factor1} + 0.209 * \text{factor2}}{2}$$

This index was then incorporated into the overall Resilience Capacity Index (RCI) under the TANGO approach.

Table 10: Factor Loadings of Adaptive Capacity.

Variables	Factor 1	Factor 2	Uniqueness
Bridging Social Capital Index	0.1037	0.6804	0.5263
Linking social capital	0.7070	0.0346	0.4989
Livelihood diversity index	0.6417	-0.0184	0.5879
Human capital index	0.3580	-0.7141	0.3619
Access to information index	0.6462	0.2669	0.5112
Bartlett test of sphericity; (Chi-square = 38.627, df = 10, p-value = 0.000)			
KMO Measure of Sampling Adequacy = 0.550			
Determinant of the correlation matrix = 0.842			
Source: Author’s computation using household survey data (2025)			

3.11. Transformative Capacity

Transformative capacity in the TANGO approach represents the broader enabling environment for long-term resilience. It was assessed using six variables: access to formal safety nets, markets, extension services, governance quality, public services, and communal natural resources. Factor analysis retained three components; explaining 60.97% of the total variance (see Appendix Table 8). As shown in Table 11, all variables showed significant loadings above 0.364, with governance, public services, and safety nets contributing most strongly. In contrast, access to markets and extension services loaded negatively, indicating structural challenges. These results are consistent with Asmamaw, Mereta, & Ambelu (2019), who emphasized the central role of transformative capacity in sustaining household resilience. Qualitative findings reinforced these results. Focus group discussions highlighted that weak infrastructure and poor access to services, such as roads, markets, health care, and

electricity directly undermine household resilience. Seasonal inaccessibility of markets was identified as a critical barrier to timely crop and livestock management and to income generation. Participants stressed that strengthening public services at kebele level would allow households to better engage in trade and agriculture, thereby reducing vulnerability to poverty and food insecurity.

The factor scores were weighted by their explained variance to compute the Transformative Capacity (TC) index:

$$TC = \frac{0.265 * \text{factor1} + 0.176 * \text{factor2} + 0.168 * \text{factor3}}{3}$$

The result obtained from this equation was further used to estimate the resilience capacity index using the TANGO approach.

Table 11: Factor Loadings of Transformative Capacity.

Variables	Factor 1	Factor 2	Factor 3	Uniqueness
Quality and responsibility of governance	0.4787	0.7331	0.1626	0.2070
Access to formal safety nets	0.7197	0.3160	-0.1983	0.3428
Access to market	-0.4985	0.3149	-0.3346	0.5404
Access to extension services	-0.4549	0.4509	-0.0900	0.5816
Access to public services index	-0.3318	0.1944	0.8642	-0.3318
Access to communal natural resource index	0.5273	-0.2878	0.2728	0.5647
Bartlett test of sphericity; (Chi-square = 54.462, df= 15, p-value = 0.000)				
Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO = 0.576)				
Determinant of the correlation matrix =0.784				
Source: Author's computation using household survey data (2025)				

3.12. Aggregating Household Resilience Capacity in the TANGO Approach

In the second stage of the TANGO approach, factor analysis was applied to estimate the overall Resilience Capacity Index (RCI) from the three latent variables: absorptive, adaptive, and transformative capacity. Statistical requirements for model adequacy were

satisfied. Bartlett's test of sphericity was significant ($\chi^2 = 16.137$, $df = 3$, $p < 0.001$), the KMO measure indicated acceptable sampling adequacy (0.500), and the determinant of the correlation matrix (0.900) confirmed no multicollinearity. Following the Kaiser rule, two factors with eigenvalues ≥ 1 were retained, together explaining 75.5% of the variance (see Appendix Table 9).

Table 12: Factor Loadings of Resilience Capacity in TANGO Methods.

Variable	Factor 1	Factor 2	Uniqueness	Corr. RCI
Absorptive capacity index	0.1218	0.9796	0.0256	0.127***
Adaptive capacity index	0.7970	0.0553	0.3617	0.778***
Transformative capacity index	-0.7802	0.2095	0.3474	-0.798***
Bartlett test of sphericity; (Chi-square = 16.137, df = 3, p-value = 0.000)				
Kaiser-Meyer-Olkin Measure of Sampling Adequacy = (KMO = 0.500)				
Determinant of the correlation matrix = 0.900				
Note: ***: Correlation is significant at the level of 0.01				

As shown in Table 12, absorptive capacity recorded the strongest factor loading (0.979) and a significant positive correlation with resilience ($r = 0.127$, $p < 0.01$), confirming its importance in cushioning households against shocks (Martin, 2019). Adaptive capacity also displayed a high positive loading (0.797) and a strong correlation with resilience (0.778, $p < 0.01$), underscoring its central role in strengthening livelihoods, as highlighted by Villoslada (2019) and d'Errico et al. (2018). In contrast, transformative capacity loaded negatively (-0.780) and correlated inversely with resilience ($r = -0.798$, $p < 0.01$), suggesting that weak governance, poor infrastructure, and limited access to public services remain dominant features of vulnerable households in the study area.

3.13. Relationships between Resilience Capacity and TANGO Dimensions

Two-way scatter plots were used to examine the relationships between the overall Resilience Capacity Index (RCI) and the three latent variables of the TANGO approach: absorptive, adaptive, and transformative capacities. As shown in Figure 4, absorptive and adaptive capacities exhibited positive correlations with the RCI, while transformative capacity showed a negative relationship. The line of best fit in each scatter plot indicated the strength and direction of these associations.

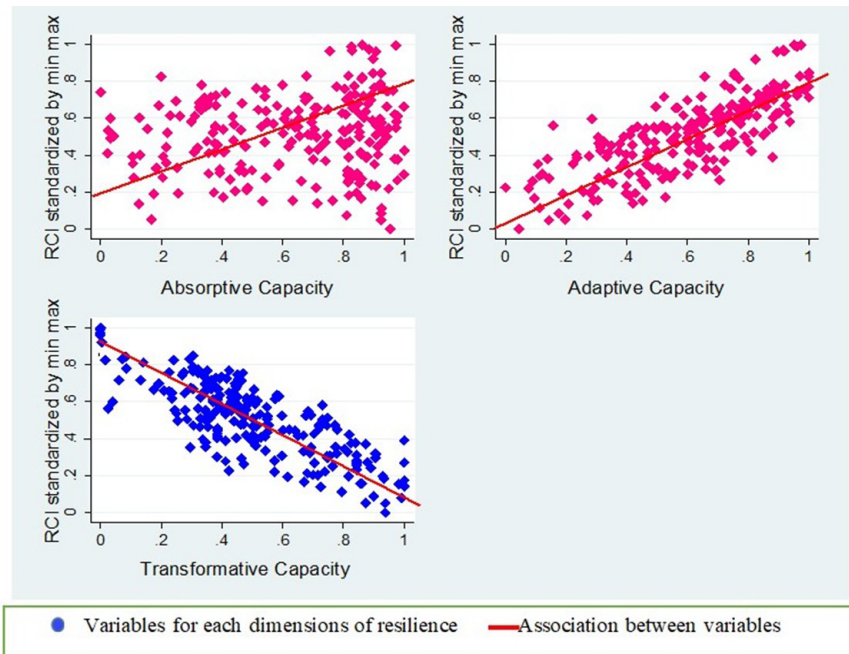


Figure 4: Scatter Plots for Resilience Capacity to Food Insecurity with TANGO Dimensions.

Overall, the factor analysis results indicate that household resilience is primarily driven by absorptive and adaptive capacities. Key contributors include bonding social capital, asset ownership, cash savings, access to informal safety nets, and disaster preparedness (absorptive), as well as bridging and linking social capital, livelihood diversity, and access to information (adaptive). This findings are consistent with Sunday et al. (2023) in Uganda, underscoring the importance of strengthening these capacities in resilience-focused interventions.

3.14. Relationships between RIMA and TANGO Measures of Resilience

Resilience capacity is multidimensional and can be measured using different empirical approaches. Among these, the Resilience Index Measurement and Analysis (RIMA) and the TANGO framework are widely applied to estimate the Resilience Capacity Index (RCI). Although they differ in variable selection and estimation techniques, RIMA relies on structural equation modeling (SEM), while TANGO applies factor analysis; the two approaches aim to capture similar resilience dimensions. Importantly, higher RCI values should correspond to a greater likelihood of household resilience (Upton et al., 2022; Villoslada, 2019).

SEM results for RIMA (Table 8) confirmed model adequacy, while the TANGO approach (Table 12) generated absorptive, adaptive, and transformative capacity indexes. When standardized to a 0–100

scale, both methods produced comparable mean values, differing by only a few points (Table 13). This consistency aligns with findings by Upton et al. (2022) and Villoslada (2019), who noted that despite methodological differences, RIMA and TANGO provide similar insights into household resilience.

Table 13: Summary Statistics of the Two Resilience Measures.

Method/ Approach	Variable	Mean	Std. Dev.	Min	Max
RIMA	Resilience Capacity Index (RCI)	.5429034	.213944	0	1
TANGO	Resilience Capacity Index (RCI)	.5138793	.205462	0	1

Source: Author’s computation using household survey data (2025)

Kernel density distributions (Figure 5) further demonstrate that both methods generate similar resilience profiles, with most households clustered around the mean but with substantial variation at the upper tail. This indicates that while some households are far more resilient than average, many remain vulnerable.

Given the absence of a universally accepted cut-off, following Demeke & Tefera (2013), the mean index was applied to classify households. Results (Table 14) show that approximately 55% of households are resilient under both approaches, while about 45% remain non-resilient. This convergence highlights the robustness of both RIMA and TANGO in capturing resilience patterns among rural Ethiopian households.

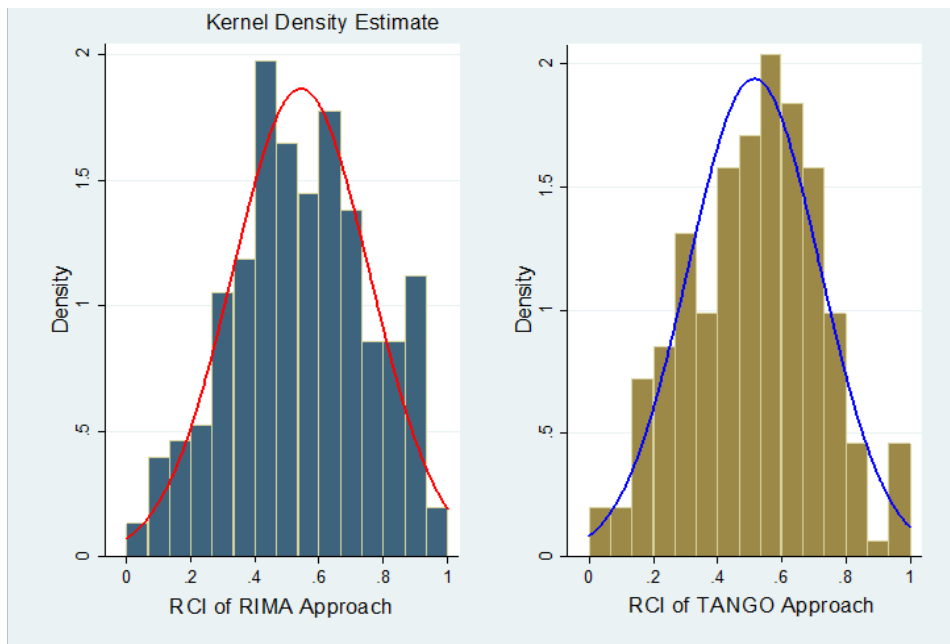


Figure 5: Distribution of Overall Resilience Capacity in RIMA and TANGO Method.

Table 14: Percentages of Household Resilience Capacity using the Two Methods.

Approach/Methods	Resilience Capacity Index (RCI)	Frequency	Percent
RIMA	Resilient	125	54.82
	Not resilient	103	45.18
	Total	228	100
TANGO	Resilient	126	55.51
	Not resilient	101	44.49
	Total	228	100

Source: Author’s computation using household survey data (2025)

4. Conclusion and Recommendations

4.1. Conclusion

The study was conducted in Mekiet District, North Wollo Zone, and rural northern Ethiopia, to assess household resilience to food insecurity using both the RIMA and TANGO approaches. The RIMA approach considered four latent variables, access to basic services, adaptive capacity, assets, and social safety nets, while, the TANGO approach focused on absorptive, adaptive, and transformative capacities. Factor analysis and Structural equation modeling were applied to estimate the resilience capacity index (RCI) for each approach. Results from RIMA indicated that, except for access to basic services, adaptive capacity, assets, and social safety nets negatively influenced resilience, suggesting that households with lower levels in these dimensions are more vulnerable to shocks. The TANGO approach revealed positive associations of absorptive and adaptive capacities with household resilience, whereas transformative capacity was negatively associated. Factor loadings

for all variables exceeded 0.364, confirming statistical significance. The average household resilience index was 0.54 for RIMA and 0.51 for TANGO, highlighting that both approaches yield comparable outcomes and effectively capture household resilience patterns.

4.2. Recommendations

Based on the findings, the following recommendations are suggested to strengthen household resilience to food insecurity:

- ✓ Since adaptive capacity emerged as a critical determinant in both RIMA and TANGO approach, resilience programs should prioritize livelihood diversification and enhancement of human capital to reduce vulnerability.
- ✓ Improving assets, adaptive capacity, and social safety nets through better resource access, risk management, and social support mechanisms can significantly enhance household resilience.
- ✓ Resilience-building initiatives should operate at district, community, and household levels to ensure comprehensive and sustainable impacts.
- ✓ Policies should aim for sustained improvements in food security, focusing on long-term outcomes rather than short-term relief.
- ✓ As this study employed a cross-sectional design, it captured resilience at a single point in time. Future research should use longitudinal data to monitor changes in household resilience over time and better inform adaptive strategies.

4.3. CRediT Authorship Contribution Statement

Tadsual Asfaw Dessie: Writing—original draft, Investigation, Formal analysis, Conceptualization, Supervision, and Writing – review & editing.

Declaration of COMPETING INTEREST: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Funding: No funding was received.

References

- Acock, A. C. (2013). *Discovering Structural Equation Modeling Using Stata*. Stata Press Books. Retrieved from <https://www.stata-press.com/books/discovering-structural-equation-modeling-using-stata>
- Ado, A. M., Savadogo, P., & Abdoul-Azize, H. T. (2019). Livelihood strategies and household resilience to food insecurity: insight from a farming community in Aguié district of Niger. *Agriculture and Human Values*, 36(4), 747–761. doi: <https://doi.org/10.1007/s10460-019-09951-0>
- Alinovi, L., D'errico, M., Mane, E., & Romano, D. (2010a). *Livelihoods Strategies and Household Resilience to Food Insecurity: An Empirical Analysis to Kenya*. European Report on Development. Retrieved from https://www.technicalconsortium.org/wp-content/uploads/2014/05/Livelihoods-Strategies_Household-Res.pdf
- Alinovi, L., Mane, E., & Romano, D. (2010b). Measuring Household Resilience to Food Insecurity: Application to Palestinian Households. In R. Benedetti, M. Bee, G. Espa, & F. Piersimoni (Eds.), *Agricultural Survey Methods* (pp. 341–368). John Wiley & Sons. doi: <https://doi.org/10.1002/9780470665480.ch21>
- Aragie, T., & Genanu, S. (2017). Level and Determinants of Food Security in North Wollo Zone (Amhara Region – Ethiopia). *Journal of Food Security*, 5(6), 232–247. doi: <https://doi.org/10.12691/jfs-5-6-4>
- Asmamaw, M., Mereta, S. T., & Ambelu, A. (2019). Exploring households' resilience to climate change-induced shocks using Climate Resilience Index in Dinki watershed, central highlands of Ethiopia. *PloS One*, 14(7), e0219393. doi: <https://doi.org/10.1371/journal.pone.0219393>
- Atara, A., Tolossa, D., & Denu, B. (2019). Assessment of food security situation of the rural households: the case of Boricha Woreda of Sidama Zone, Ethiopia. *GeoJournal*, 86(2), 711–727. doi: <https://doi.org/10.1007/s10708-019-10094-2>
- Atara, A., Tolossa, D., & Denu, B. (2020). Analysis of rural households' resilience to food insecurity: Does livelihood systems/choice/ matter? The case of Boricha woreda of sidama zone in southern Ethiopia. *Environmental Development*, 35, 100530. doi: <https://doi.org/10.1016/j.envdev.2020.100530>
- Bayram, N. (2013). *Yapısal eşitlik modellemesine giriş [Introduction to structural equation modeling]*. Bursa: Ezgi Kitabevi.
- Berhanu, W., Colman, D., & Fayissa, B. (2007). Diversification and livelihood sustainability in a semi-arid environment: A case study from southern Ethiopia. *The Journal of Development Studies*, 43(5), 871–889. doi: <https://doi.org/10.1080/00220380701384554>
- Beyene, A., Gebru, K. M., Hailekiros, T., & Gebreegziabher, A. (2024). Household Food Security Status and Its Determinant: Case of Atsbi District, Tigray Regional state, Ethiopia. *Journal of Food Security*, 12(3), 59–65. doi: <https://doi.org/10.12691/jfs-12-3-4>
- Beyene, F., Senapathy, M., Bojago, E., & Tadiwos, T. (2023). Rural household resilience to food insecurity and its determinants: Damot Pulasa district, Southern Ethiopia. *Journal of Agriculture and Food Research*, 11, 100500. doi: <https://doi.org/10.1016/j.jafr.2023.100500>
- Bezu, D. C. (2018). A Review of Factors Affecting Food Security Situation of Ethiopia: From the Perspectives of FAD, Economic and Political Economy Theories. *International Journal of Agriculture Innovations and Research*, 6(6), 2319–2473. Retrieved from https://ijair.org/administrator/components/com_jresearch/files/publications/IJAIR_2769_FINAL.pdf
- Bollen, K. A. (2002). Latent Variables in Psychology and the Social Sciences. *Annual Review of Psychology*, 53(1), 605–634. doi: <https://doi.org/10.1146/annurev.psych.53.100901.135239>
- Bollen, K. A., & Hoyle, R. H. (2012). Latent Variables in Structural Equation Modeling. In R. H. Hoyle (Ed.), *Handbook of Structural Equation Modeling* (pp. 56–67). The Guilford Press.
- Bollen, K. A., Kirby, J. B., Curran, P. J., Paxton, P. M., & Chen, F. (2007). Latent Variable Models Under Misspecification: Two-Stage Least Squares (2SLS) and Maximum Likelihood (ML) Estimators. *Sociological Methods & Research*, 36(1), 48–86. doi: <https://doi.org/10.1177/0049124107301947>
- Borku, A. W., Utallo, A. U., & Tora, T. T. (2024). Determinants of urban household vulnerability to food insecurity in southern Ethiopia. *Discover Food*, 4(1), 37. doi: <https://doi.org/10.1007/s44187-024-00110-x>



- Carter, M. R., Little, P. D., Mogues, T., Negatu, W., & Ababa, A. (2006). *The Long-Term Impacts of Short-Term Shocks: Poverty Traps and Environmental Disasters in Ethiopia and Honduras*. Basis Brief 28. International Food Policy Research Institute. Retrieved from <https://www.researchgate.net/publication/267198252>
- Çelik, H. E., & Yilmaz, V. (2013). *Structural Equation Modeling with LISREL 9.1, Basic Concepts–Applications–Programming*. Ankara: Ani Yayincilik.
- Ciani, F., & Romano, D. (2014). Testing for Household Resilience to Food Insecurity: Evidence from Nicaragua. In *EAAE Congress* (pp. 26–29). doi: <https://doi.org/10.22004/ag.econ.172958>
- Clay, E. (2003). Food Security: Concepts and Measurement. In *Trade Reforms and Food Security: Conceptualising the Linkages* (pp. 25–34). FAO. Retrieved from <https://www.researchgate.net/publication/285667097>
- Cochran, W. G. (1977). *Sampling Techniques*. John Wiley & Sons.
- Constas, M., & Barrett, C. (2013). Principles of Resilience Measurement for Food Insecurity: Metrics, Mechanisms, and Implementation Plans. In *Expert Consultation on Resilience Measurement Related to Food Security*. Rome: Food and Agricultural Organization and World Food Program.
- Constas, M. A., Frankenberger, T. R., & Hoddinott, J. (2014). *Resilience Measurement Principles: Toward an Agenda for Measurement Design* (FSIN Technical Series No. 1). WFP. Retrieved from https://www.fsnnetwork.org/sites/default/files/fsin_paper1.pdf
- d’Errico, M., Romano, D., & Pietrelli, R. (2018). Household resilience to food insecurity: evidence from Tanzania and Uganda. *Food Security*, 10(4), 1033–1054. doi: <https://doi.org/10.1007/s12571-018-0820-5>
- Demeke, M., & Tefera, N. (2013). *Sustainable Resilience for Food and Nutrition Security: The Case of Farming Rural Households in Ethiopia*. Agricultural Development and Economics Division (ESA), Food and Agricultural Organization (FAO): Rome, Italy.
- DiStefano, C., Zhu, M., & Mindrila, D. (2009). Understanding and Using Factor Scores: Considerations for the Applied Researcher. *Practical Assessment, Research, and Evaluation*, 14(1), 20. doi: <https://doi.org/10.7275/da8t-4g52>
- FAO. (2014). *Resilience Index Measurement and Analysis (RIMA) Model*. Food and Agriculture Organization of the United Nation, rome, Italy.
- FAO. (2016). *RIMA-II, Resilience Index Measurement and Analysis—II*. Food and Agriculture Organization of the United Nations: Rome, Italy. Retrieved from <https://openknowledge.fao.org/server/api/core/bitstreams/c61a9a8c-feb4-4199-8cb1-7085c84908c8/content>
- FAO. (2018). *The Impact of Disasters and Crises on Agriculture and Food Security 2017*. FAO Rome. Retrieved from <https://www.fao.org/in-action/kore/publications/publications-details/en/c/1107398>
- FAO. (2020). *The State of Food Security and Nutrition in the World 2020*. FAO. Retrieved from <https://www.fao.org/3/ca9692en/CA9692EN.pdf>
- FAO, IFAD, UNICEF, WFP, & WHO. (2019). *The State of Food Security and Nutrition in the World 2019: Safeguarding Against Economic Slowdowns and Downturns*. Rome, FAO. Retrieved from <https://cdn.who.int/media/docs/default-source/nutritionlibrary/publications/state-food-security-nutrition-2019-en.pdf>
- FAO, IFAD, UNICEF, WFP, & WHO. (2024). *The State of Food Security and Nutrition in the World 2024 – Financing to end hunger, food insecurity and malnutrition in all its forms*. Rome. doi: <https://doi.org/10.4060/cd1254en>
- Field, A. (2009). Correlation: Bivariate Correlation. In *Field: A Discovering Statistics using SPSS* (pp. 175–179). British Library: London, UK.
- Frankenberger, T., & Smith, L. C. (2015). *Ethiopia Pastoralist Areas Resilience Improvement and Market Expansion (PRIME) Project Impact Evaluation: Report of the Interim Monitoring Survey 2014-2015*. USAID: Washington DC, USA. Retrieved from https://www.fsnnetwork.org/sites/default/files/prime_ie_report_2015.pdf
- Gambo Boukary, A., Diaw, A., & Wünscher, T. (2016). Factors Affecting Rural Households’ Resilience to Food Insecurity in Niger. *Sustainability*, 8(3), 181. doi: <https://doi.org/10.3390/su8030181>
- Goshu, M. T. (2016). *Determinants of Rural Food Security and Child Nutritio*. Aligarh Muslim University Aligarh, India.
- Guyu, D. F., & Muluneh, W.-T. (2015). Wild foods (plants and animals) in the green famine belt of Ethiopia: Do they contribute to household resilience to seasonal food insecurity? *Forest Ecosystems*, 2(1), 34. doi: <https://doi.org/10.1186/s40663-015-0058-z>

- Harika, R., Faber, M., Samuel, F., Mulugeta, A., Kimiywe, J., & Eilander, A. (2017). Are Low Intakes and Deficiencies in Iron, Vitamin A, Zinc, and Iodine of Public Health Concern in Ethiopian, Kenyan, Nigerian, and South African Children and Adolescents? *Food and Nutrition Bulletin*, 38(3), 405–427. doi: <https://doi.org/10.1177/0379572117715818>
- Henly-Shepard, S., & Sagara, B. (2018). *Resilience Measurement Practical Guidance Note Series: An Overview. Produced by Mercy Corps as part of the Resilience Evaluation. Analysis and Learning (REAL) Associate Award.*
- Huber, C. (2014). *Introduction to Structural Equation Modeling Using Stata.* California Association for Institutional Research. Retrieved from <https://cair.org/wp-content/uploads/sites/474/2015/07/HuberC-SEMWorkshop.pdf>
- Kaiser, H. F. (1960). The Application of Electronic Computers to Factor Analysis. *Educational and Psychological Measurement*, 20(1), 141–151. doi: <https://doi.org/10.1177/001316446002000116>
- Kasie, T., Agrandio, A., Adgo, E., & Garcia, I. (2017). *Household resilience to food insecurity: Shock exposure, livelihood strategies and risk response options: The case of Tach-Gayint District, Amhara Region, Ethiopia* (Doctoral dissertation, University of Jaume I). Retrieved from <https://www.tdx.cat/handle/10803/525850>
- Kebede, T., Haji, J., Legesse, B., & Mammo, G. (2016). *Evaluation of rural households' food security through resilience indicators in West Shoa, Ethiopia.* 5th International Conference of the African Association of Agricultural Economists, September 23-26, 2016, Addis Ababa, Ethiopia. doi: <https://doi.org/10.22004/ag.econ.246978>
- Knippenberg, E., Jensen, N., & Constanas, M. (2019). Quantifying household resilience with high frequency data: Temporal dynamics and methodological options. *World Development*, 121, 1–15. doi: <https://doi.org/10.1016/j.worlddev.2019.04.010>
- Lascano Galarza, M. X. (2020). Resilience to Food Insecurity: Theory and Empirical Evidence from International Food Assistance in Malawi. *Journal of Agricultural Economics*, 71(3), 936–961. doi: <https://doi.org/10.1111/1477-9552.12397>
- Liyew, D. M., & Damtie, Y. A. (2024). Determinants of urban household income diversification and its relation to food security: lessons from Yejube town in Ethiopia. *Cogent Social Sciences*, 10(1), 2368946. doi: <https://doi.org/10.1080/23311886.2024.2368946>
- Martin, S. (2019). *Somalia Resilience Recurrent Monitoring Survey (RMS) Report.* Washington, DC: The Resilience Evaluation, Analysis and Learning (REAL) Associate Award. Retrieved from <https://www.fsnnetwork.org/resource/somalia-resilience-recurrent-monitoring-survey-rms-report>
- Maxwell, D., Vaitla, B., Tesfay, G., & Abadi, N. (2013). *Resilience, Food Security Dynamics and Poverty Traps in Northern Ethiopia. Analysis of a Biannual Panel Data Set, 2011–2013.* Somerville: Tufts University/Feinstein International Center. Retrieved from <https://fic.tufts.edu/wp-content/uploads/Resilience-Food-Security-Dynamics.pdf>
- McGuire, S. (2015). FAO, IFAD, and WFP. The State of Food Insecurity in the World 2015: Meeting the 2015 International Hunger Targets: Taking Stock of Uneven Progress. Rome: FAO, 2015. *Advances in Nutrition*, 6(5), 623–624. doi: <https://doi.org/10.3945/an.115.009936>
- Mohamed, A. A. (2017). Food Security Situation in Ethiopia: A Review Study. *International Journal of Health Economics and Policy*, 2(3), 86–96. doi: <https://doi.org/10.11648/j.hep.20170203.11>
- MWADO. (2024). *Mekiet Woreda Administration office: Descriptions of the study district, Mekiet, North Wollo.* Ethiopia: Amhara.
- Naing, L., Winn, T., & Rusli, B. N. (2006). Practical Issues in Calculating the Sample Size for Prevalence Studies. *Archives of Orofacial Sciences*, 1, 9–14. Retrieved from https://aos.usm.my/docs/Vol_1/09_14_ayub.pdf
- Negash, T. (2019). *Pictures of Food Insecurity in Amhara Region.*
- Negussie, M. (2010). *Household Resilience to Food Insecurity in Ethiopia: Panel Data Evidence.* mimeo.
- Odum, M. (2011). *Factor Scores, Structure and Communalities Coefficients: A Primer.* Texas A&M University, College Station. Retrieved from <https://files.eric.ed.gov/fulltext/ED529102.pdf>
- Schumacker, R. E., & Lomax, R. G. (2004). *A Beginner's Guide to Structural Equation Modeling* (2nd ed.). Lawrence Erlbaum Associates Publishers.
- Siyum, N., Giziew, A., & Abebe, A. (2022). Factors influencing adoption of improved bread wheat technologies in Ethiopia: empirical evidence from Meket district. *Heliyon*, 8(2), e08876. doi: <https://doi.org/10.1016/j.heliyon.2022.e08876>

- Smith, L. C., & Frankenberger, T. R. (2018). Does Resilience Capacity Reduce the Negative Impact of Shocks on Household Food Security? Evidence from the 2014 Floods in Northern Bangladesh. *World Development*, 102, 358–376. doi: <https://doi.org/10.1016/j.worlddev.2017.07.003>
- Sunday, N., Kahunde, R., Atwine, B., Adelaja, A., & George, J. (2023). How specific resilience pillars mitigate the impact of drought on food security: Evidence from Uganda. *Food Security*, 15(1), 111–131. doi: <https://doi.org/10.1007/s12571-022-01313-9>
- Tabachnick, B. G., & Fidell, L. S. (2007). *Using Multivariate Statistics* (5th ed.). Boston: Allyn and Bacon.
- Tefera, M. (2014). *Resilience to drought induced food insecurity shocks: The case of Borena pastoral communities in Dire and Yabello Districts, Oromia, Ethiopia* (Doctoral dissertation, A thesis submitted to the Center for Food Security Studies College of Development Studies).
- Tefera, N., & Kayitakire, F. (2014). Household Resilience for Food and Nutrition Security: Empirical Evidence From Rural Household in Ethiopia. In *Information For Meeting African's Transformation And Food Security Goals – IMAAFS*. Retrieved from <https://www.researchgate.net/publication/269872488>
- Telila, H. F., & Sima, E. A. (2024). Quantifying food insecurity in Ethiopia: Prevalence, drivers, and policy implications. *Cogent Social Sciences*, 10(1), 2318862. doi: <https://doi.org/10.1080/23311886.2024.2318862>
- Toma, T. M., Andargie, K. T., Alula, R. A., Kebede, B. M., & Gujo, M. M. (2023). Household food insecurity and associated factors in South Ari district, Southern Ethiopia: A community-based cross-sectional study. *PloS One*, 18(4), e0284252. doi: <https://doi.org/10.1371/journal.pone.0284252>
- Upton, J., Constenla-Villoslada, S., & Barrett, C. B. (2022). Caveat utilitor: A comparative assessment of resilience measurement approaches. *Journal of Development Economics*, 157, 102873. doi: <https://doi.org/10.1016/j.jdeveco.2022.102873>
- Vaitla, B., Tesfay, G., Rounseville, M., & Maxwell, D. (2012). *Resilience and Livelihoods Change in Tigray, Ethiopia*. Somerville, MA: Tufts University, Feinstein International Center. Retrieved from <https://fic.tufts.edu/wp-content/uploads/Resilience-and-Livelihoods-Change-in-Tigray-FINAL-30-10-12.pdf>
- Villoslada, S. C. (2019). *Development Resilience: A Comparison of Popular Measurement Methods*. Cornell University.
- Wassie, S. B., Mengistu, D. A., Birlie, A. B., & Waktola, D. K. (2023). Drought-induced agricultural livelihood vulnerability: Livelihood-based comparative analysis in Northeast highlands of Ethiopia. *Cogent Food & Agriculture*, 9(1), 2238981. doi: <https://doi.org/10.1080/23311932.2023.2238981>
- Welderufael, M. (2014). Determinants of Households Vulnerability to Food Insecurity in Ethiopia: Econometric analysis of Rural and Urban Households. *Journal of Economics and sustainable Development*, 5(24), 70–79. Retrieved from <https://www.iiste.org/Journals/index.php/JEDS/article/view/17506>
- WFP. (2024). *Annual Country Report 2024: Ethiopia*. World Food Programme. Retrieved from <https://docs.wfp.org/api/documents/WFP-0000165429/download/>
- Wubetie, H. T., Zewotir, T., Mitku, A. A., & Dessie, Z. G. (2023). Household food insecurity levels in Ethiopia: quantile regression approach. *Frontiers in Public Health*, 11, 1173360. doi: <https://doi.org/10.3389/fpubh.2023.1173360>
- Wuensch, K. L. (2016). An introduction to path analysis. *Introduction to path analysis*, 1–18. Retrieved from <https://www.researchgate.net/profile/J-Tarafdar/post/Residual-point-from-path-analysis/attachment/59d6505779197b80779a937c/AS%3A502485996326912%401496813405091/download/Path.pdf>
- Yohannes, G., Wolka, E., Bati, T., & Yohannes, T. (2023). Household food insecurity and coping strategies among rural households in Kedida Gamela District, Kembata-Tembaro zone, Southern Ethiopia: mixed-methods concurrent triangulation design. *BMC Nutrition*, 9(1), 4. doi: <https://doi.org/10.1186/s40795-022-00663-z>
- Yong, A. G., & Pearce, S. (2013). A Beginner's Guide to Factor Analysis: Focusing on Exploratory Factor Analysis. *Tutorials in Quantitative Methods for Psychology*, 9(2), 79–94. doi: <https://doi.org/10.20982/tqmp.09.2.p079>

Appendix

Table 1: Eigenvalue and Proportions of Access to basic Services.

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.98529	0.68974	0.3309	0.3309
Factor2	1.29555	0.09759	0.2159	0.5468
Factor3	1.19796	0.40519	0.1997	0.7465
Factor4	0.79276	0.33087	0.1321	0.8786
Factor5	0.46189	0.19535	0.0770	0.9556
Factor6	0.26654	.	0.0444	1.0000

LR test: independent vs. saturated: $\chi^2(15) = 270.55$ Prob> $\chi^2 = 0.0000$

Table 2: Eigenvalue and Proportions of Adaptive Capacity.

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.39550	0.36863	0.3489	0.3489
Factor2	1.02687	0.19444	0.2567	0.6056
Factor3	0.83243	0.08722	0.2081	0.8137
Factor4	0.74521	.	0.1863	1.0000

LR test: independent VS. saturated: $\chi^2(6) = 26.59$ Prob> $\chi^2 = 0.0002$

Table 3: Eigenvalue and Proportions of Asset Index.

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.34854	0.32923	0.3371	0.3371
Factor2	1.01932	0.08514	0.2548	0.5920
Factor3	0.93418	0.23622	0.2335	0.8255
Factor4	0.69796	.	0.1745	1.0000

LR test: independent vs. saturated: $\chi^2(6) = 24.73$ Prob> $\chi^2 = 0.0004$

Table 4: Eigenvalue and Proportions of Social Safety Nets.

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1Comp2	1.35594.644058	.711884.	0.67800.3220	0.67801.0000

Table 5: Results of SEM of Resilience Capacity in RIMA Approach.

	Coef.	OIM Std. Err.	z	P> z	[95% Conf. Interval]	
Measurement	1	(constrained)				
mmx_absr <- rci_cons	.7052041	.0194711	36.22	0.000	.6670415	.7433667
mmx_ac <-rci_cons	-1.45245	.3132427	-4.64	0.000	-2.066394	-.8385053
	.3266277	.0192927	16.93	0.000	.2888147	.3644408
mmx_ass <-rci_cons	-.665233	.2086744	-3.19	0.001	-1.074227	-.2562386
	.3851797	.016286	23.65	0.000	.3532597	.4170998
mmx_ssn_index <-rci_cons	-.9941687	.2467124	-4.03	0.000	-1.477716	-.5106212
	.2026555	.0127876	15.85	0.000	.1775923	.2277186
var(e.mmx_absr)	.0700285	.0076589			.0565171	.0867701
var(e.mmx_ac)	.0502418	.0090355			.0353171	.0714736
var(e.mmx_ass)	.0532109	.0054358			.0435557	.0650065
var(e.mmx_ssn_index)	.0210624	.0041236			.0143502	.0309142
var(rci)	.0164115	.006178			.0078473	.0343222

Table 6: Eigenvalues and Proportions of Absorptive Capacity.

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.69939	0.63935	0.3399	0.3399
Factor2	1.06003	0.13541	0.2120	0.5519
Factor3	0.92462	0.24081	0.1849	0.7368
Factor4	0.77838	.	0.1557	0.8925
Factor5	0.53758	.	0.1075	1.0000

LR test: independent vs. saturated: $\chi^2(10) = 81.41$ Prob> $\chi^2 = 0.0000$

Table 7: Eigenvalues and Proportions of Adaptive Capacity.

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.46817	0.42256	0.2936	0.2936
Factor2	1.04561	0.04682	0.2091	0.5028
Factor3	0.99879	0.19176	0.1998	0.7025
Factor4	0.80703	0.12663	0.1614	0.8639
Factor5	0.68041	.	0.1361	1.0000

LR test: independent vs. saturated: $\chi^2(10) = 38.80$ Prob> $\chi^2 = 0.0000$

Table 8: Eigenvalues and Proportions of Transformative Capacity.

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.59062	0.53016	0.2651	0.2651
Factor2	1.06046	0.05334	0.1767	0.4418
Factor3	1.00712	0.13269	0.1679	0.6097
Factor4	0.87443	0.03920	0.1457	0.7554
Factor5	0.83522	0.20308	0.1392	0.8946
Factor6	0.63215	.	0.1054	1.0000

LR test: independent vs. saturated: $\chi^2(15) = 54.70$ Prob> $\chi^2 = 0.0000$

Table 9: Eigenvalues and Proportions of Resilience Capacity in TANGO Approach.

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.25883	0.25233	0.4196	0.4196
Factor2	1.00649	0.27181	0.3355	0.7551
Factor3	0.73468	.	0.2449	1.0000

LR test: independent vs. saturated: $\chi^2(3) = 16.21$ Prob> $\chi^2 = 0.0000$