Journal of Agriculture and Environmental Sciences

Research Article

Agroecological variations in the rural household resilience to climate change in Gubalafto District, Ethiopia

Melkamu Sete Wereta[1 2*], *Zemen Ayalew Ayele*[3] *and Yilebes Addisu Damtie*[1]

[1, 2]Institute of Disaster Risk Management and Food Security Studies, Bahir Dar University, Bahir Dar, Ethiopia
[2]College of Agriculture, Woldia University, Woldia, Ethiopia
[3]Department of Agricultural Economics, College of Agriculture and Environmental Science, Bahir Dar University, P.O. Box 5501, Bahir Dar, Ethiopia
***Corresponding author:** melkamusete@gmail.com

Received: August 01, 2025; Accepted: November 30, 2025

Abstract: *Climate change poses significant challenges for rural households, particularly in farming communities, leading to crop loss and reduced incomes that threaten livelihoods. This study analyzed resilience capacity of rural households to climate change, the case of Gubalafto distracts, Ethiopia. Moreover, the study examined the effect of agroecological differences on the households' resilience level. The study utilized a survey research design, in which gathering data from 355 households selected through random surveys. Principal component analysis, analysis of covariance, and descriptive statistics were employed to analyze the data. This study presents an estimation of the overall household resilience capacity, derived from three key dimensions of resilience: absorptive, adaptive, and transformative capacities. The analysis revealed significant loadings for these dimensions, with values of 0.612, 0.534, and 0.583, respectively, indicating their importance in building resilience capacity. Moreover, findings reveal that 44% of households were found to be have a low resilience capacity index (RCI), while 37% and 19% were a medium, high, with an overall mean RCI of 0.33. Surprisingly, lowland households demonstrated a higher average climate resilience score compared to midland and highland households, with p-values of 0.02 and 0.001, respectively. However, no significant difference was found between midland and highland households. Relevant institutions should prioritize investments in communication infrastructure, institutional services, and social safety nets. Particular emphasis should be given due emphasis to highland and midland agro-ecological zones, where targeted support is essential for strengthening household resilience capacities.*

Keywords: Agroecology, Absorptive capacity, Resilience capacity, Rural household

Citation: Wereta, M.S., Ayele, Z.A., and Damtie, Y.A. (2025). Agroecological Variations in Rural Household Resilience to Climate Change in Gubalafto District, Ethiopia. *J. Agric. Environ. Sci.* 10(2): 128-148. https://doi.org/10.63990/jaes.v10i2.12174

1. Introduction

Climate change has emerged as a formidable development constraint, with far-reaching impacts on ecosystems, agricultural systems, and vulnerable communities. It leads to erratic rainfall, soil degradation, pest outbreaks, and extreme weather events including floods, droughts, and heat waves which collectively undermine food production and weaken rural resilience (Fadairo et al., 2020; IPCC, 2021). These climatic disruptions are particularly severe in developing regions, where rural populations depend heavily on rain-fed agriculture. In such contexts, agricultural yield reductions and livelihood instability exacerbate poverty, food insecurity, diminished adaptive capacity, and social vulnerability security (Harvey et al., 2018; Shi et al., 2022). Although Africa has contributed minimally to global greenhouse gas emissions, the continent has suffered significant loss and damage across key development sectors due to human-induced climate change. Rural farmers, in particular, are among the hardest hit, facing severe threats to both food and livelihood security (Ayugi et al., 2022; Harvey et al., 2018). According to Jiri et al. (2022), prolonged droughts, flooding, and unpredictable rainfall patterns severely weaken farmers' resilience capacity Hence, addressing these challenges requires integrated development interventions that enhance climate resilience, safeguard food systems, and empower rural communities.

Ethiopia, the second most populous country in Africa, has a diverse climate with varying rainfall patterns (Koo et al., 2019). The agricultural sector, which is crucial for the livelihoods of rural communities, is significantly impacted by climate change (Belay et al., 2017). The country has a history of drought, experiencing an increase in extreme weather events, including the meteorological droughts of the 1970s and the 2015/2016 El Niño, which caused crop failures, acute food shortages, and weakened household resilience (Kosmowski, 2018; Green, 2019; Bahta and Myeki, 2022). This situation weakens households' ability to cope and resilience capacity to climate change (WFP and CSSA, 2022). This makes the country susceptible to challenges including drought, flood, and land degradation, which impede its ability to respond effectively to climate-related threats (Mekonnen et al., 2021). In brief, climate change poses escalating threats to rural livelihoods and food security, particularly in Ethiopia, where limited adaptive capacity that underscores the urgent need for resilience-focused development.

As a result, the concept of resilience has emerged as a plausible framework for improving the capacity to withstand shocks and stressors (Frankenberger and Nelson, 2013). The United Nations Office for Disaster Risk Reduction (UNDRR) defines resilience as the capacity of a system, community, or society facing hazards to effectively and promptly resist, absorb, adapt to, and recover from their impacts (Nguyen and Akerkar, 2020). In practical terms, resilience often refers to the ability of socioecological systems to respond to and adapt to new conditions, particularly in the context of climate change. Studies emphasize a socioecological perspective, which not only values the ability to withstand disturbance but also encourages adaptation and transformation (Walker and Salt, 2012). This approach, known as resilience thinking, focuses on three key aspects of socioecological systems: resilience as persistence, adaptability, and transformability. According to Jiri et al. (2022), resilience is built through the development of diverse adaptive capacities, enabling farmers to withstand the uncertainties of a rapidly changing climate. In the 3-D Resilience Framework, Bene et al. (2012), propose that resilience emerges as the result of three capacities: absorptive, adaptive and transformative capacities. Each capacity leads to a different outcome: persistence, incremental adjustment, or transformational responses. The framework is the fact that resilience emerges as the result, not of one but all of these three capacities: absorptive, adaptive, and transformative capacities. As noted by Oxfam (2017), absorptive capacity is the ability to take deliberate protective measures and to withstand known shocks and stress. Conversely, adaptive capacity demonstrates the actions taken by households to withstand shocks during climate stress, while transformative capacity is the ability of a social system to foresee, absorb, and adopt to climate extremes and disasters by adapting transformative policies that alter the institutional rules of the game (Béné et al., 2014).

Households across agroecological zones face distinct climate risks and soil conditions that shape their resilience. Highland areas benefit from better rainfall and fertility but suffer erosion, while lowlands endure drought and heat stress. These differences directly influence resilience outcomes, including food security, income stability, and recovery capacity (Aboye et al., 2023). A study conducted in Mekiet district, Amhara region, revealed significant variation in household resilience to food insecurity across agroecological zones. Households located in midland areas demonstrated higher resilience scores, largely attributed to diversified cropping systems and improved access to agricultural services, whereas those in lowland zones faced greater vulnerability due to limited diversification and service constraints (Tofu et al., 2023b). Northern Ethiopia, particularly Gubalafto Woreda faced with erratic rainfall, droughts, and land degradation all of which undermine agricultural productivity and food security. Despite local resilience efforts, limited access to climate-smart adaptation and weak institutional support hinder progress. In response, households have adopted adaptive strategies such as off-farm income generation, small-scale irrigation, and productive safety net program (PSNP), and enhanced climate awareness. In study area, household resilience is shaped by access to institutions, sustainable land practices, and internal decision-making dynamics (DEEP, 2025; Tefera, 2021).

Literature on households' resilience capacity is found globally, for instance Ali et al. (2023), examine the impact of Climate-Smart Agriculture (CSA) on household resilience, but the study's limited disaggregate resilience outcomes across agroecology. Atara et al. (2020) and Teklu et al. (2023), examine household resilience capacity, but offer limited insight into how absorptive, adaptive, and transformative capacities contribute to overall resilience. Jayadas and Ambujam (2021), developed a farmer resilience index for coastal Tamil Nadu, but its limited sample size and narrow focus on physical-economic indicators, with less attention to institutional and social dimensions. As described in Antwi-Agyei et al. (2013), it is important to conduct community-level assessments of resilience because households vary widely in their characteristics. Hence, there is a pressing need to understand which agroecology has successes resilience capacity and to implement location-specific adaptation strategies for enhance resilience capacity of rural households. Overall, the current study is relevant because of climate change significantly affects rural livelihoods, where agriculture is predominantly rain-fed and highly sensitive to climatic shocks. By examining households' resilience capacities (absorptive, adaptive, and transformative): this study provides insights into how rural communities cope with, adapt to, and transform in response to climate-related risks. Understanding these capacities is critical for identifying vulnerable households and designing interventions that improve resilience and food security.

This study seeks to fill the above gaps by estimating household resilience to climate change (absorptive, adaptive, and transformative capacities) in the Gubalafto Woreda of Ethiopia. Specifically: It identifies the factors influencing households' resilience capacity, assesses the current level of household resilience to climate change, and examines variations in household resilience across agroecological zones.

2. Materials and Methods

2.1. Description of the study area

This research was carried out in the Gubalafto district (Figure 1), situated in the southern region of the North Wollo Zone, Ethiopia. As reported by Asnake and Elias (2017), Gubalafto district lies between 39°06'09" and 39°45'58" East longitude, and 11°34'54" and 11°58'59" North latitude. The district's landscape is primarily defined by a series of mountains, hills, and valleys, with elevations ranging from 1,379 to 3,809 meters above sea level. It experiences annual rainfall between 800 mm and 1,200 mm, along with average yearly temperatures of 21°C to 25°C. The study area faced with erratic rainfall, droughts, and land degradation all of which undermine agricultural productivity and food security. Despite local resilience efforts, limited access to climate-smart adaptation and weak institutional support hinder progress (DEEP, 2025).

Land use pattern of the Woreda includes arable land (34.1%), grazing land (17.9%), forest (27.1%), and water bodies (6%), rocky land (5%) and others (9.9%) respective (Mengistie and Kidane, 2016). According to population projections from Ethiopian Statistical Service (2022) the study area has a total population of 172,818, composed of 87,027 males and 85,791 females. Gubalafto covering an area of 900.49 square kilometers and has a population density of 191 individuals per square kilometer.

As reported by Andualem (2016), the major household economy of the study area is mixed crop-livestock farming. For instance, key crops grown in the area are barley, wheat, teff, and sorghum and households engage in livestock rising, dairy farming, and fattening of animals such as chickens, cattle, goats, and sheep to enhance their income.

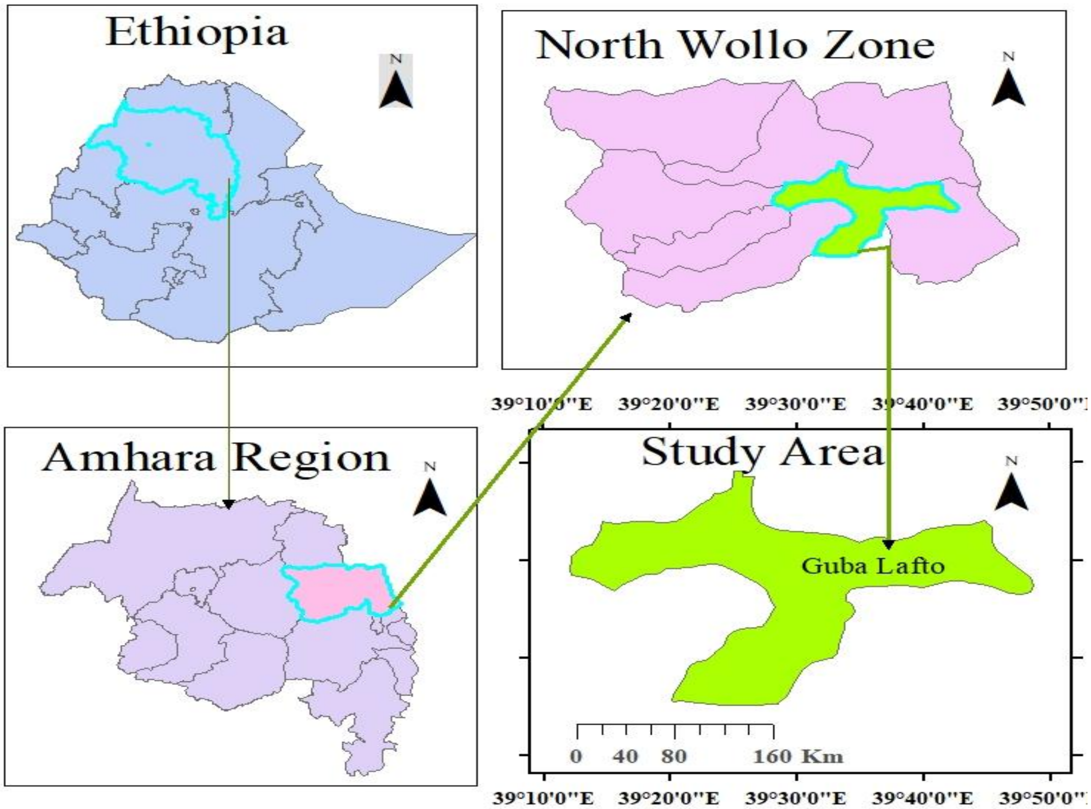

Figure 1: Location map of the study area; Source: Authors visualization, 2024

2.2. Sampling techniques

Sampling aims to examine a representative subset of a clearly defined population to draw inferences about the whole population (Gilbert and Stoneman, 2015). In doing so, researchers jointly applied purposive and multistage random sampling techniques to select study sites and representative households. Multistage cluster sampling is used to ensure the inclusion of specific groups of interest across meaningful clusters. As a probability-based method, it involves dividing the population into smaller units (Woreda's Kebeles cluster into lowlands, midlands, and highlands), allowing the proportional selection of respondents.

First, Gubalafto district was selected as the study area through purposive sampling due to climate vulnerability, agro-ecological diversity, and low adaptive capacity (DEEP, 2025) which indicating the need for further research. This non-probability sampling technique is appropriate when the researcher seeks to gain in-depth understanding from a location that exhibits specific characteristics aligned with the study focus. In the second stage, Gubalafto Woreda is classified into three agroecological zones on the basis of altitude and crop growing period: lowlands (500–1,500 m.a.s.l.) with over 210 days suitable for drought-tolerant crops; midland) (1,500–2,300 m.a.s.l.) with 150–210 days of diverse cereal and legume growth and highland (2,300–3,200 m.a.s.l.) with less than 150 days, favoring cool-climate crops such as barley and highland pulses. This classification aligns with MoA (2022). Furthermore, based on existing administrative system, Gubalafto Woreda is clustered into kebeles, with relatively even distributions across the highland, midland, and lowland zones. Hence, via lottery-based sampling, one kebele was randomly selected from each agroecological cluster, ensuring representation of the respective zones. The selected kebeles were Masso-Dengolla (highland), Gedo-Ber (midland), and Doro-Gibr (lowland). Finally, sample households were selected from the chosen kebeles through systematic sampling, using household lists available at kebele administration offices as the sampling frame.

In the literature, various methods are available for determining sample size, each suited to specific research contexts: Cochran (1963) formula is used when the population is large or infinite and the estimated proportion is known. It is widely used in surveys involving categorical data. KoThari (2004), formula applies to finite populations with a known proportion. The Yamane (1967) formula is applied when the population size is finite and known, but the estimated proportion is unknown. It is particularly useful in development studies where detailed population parameters may not be available.

In this study area, the estimated proportion of the population was unknown, and the population was assumed to be relatively uniform in characteristics relevant to the study. Therefore, the Yamane (1967) sample size formula was employed.

$$\mathrm{N} = \frac{N}{1+N*e^{2}.} \quad (1)$$

$$\mathrm{n} = \frac{3163}{1+3163*0.05^{2}.} = 355$$

Where n = the sample size, N = the total number of households in all Kebeles, and e is margin error (5%) at the 95% confidence level.

After the total sample size was determined, sample households were selected from each kebele via proportional allocation on the basis of their respective population sizes (Table1).

$$\mathrm{ni} = \frac{\mathrm{n}*N}{\sum Ni} \quad (2)$$

Where n is the sample size, ni is the required sample size in the ith Kebele, N is the total number of households across all Kebeles, and Ni is the total number of households in the ith Kebele.

Table 1: Number of sampled households

Woreda	Agroecological zone	Kebeles	Total household	Sampled household
Gubalafto	Highland	Masso-dengolla	1093	123
	Midland	Gedo-ber	908	102
	Lowland	Doro-gibr	1162	130
Total			3163	**355**

2.3. Methods of data collection

The study employed both primary and secondary data sources, with a primary emphasis on firsthand data collected from selected rural households within the study area. Primary data were obtained through a household survey; focus group discussions (FGDs), and key informant interviews (KII). A combination of semi- structured questionnaire, focus group discussions, and key informant interviews checklist were was used to gather both quantitative and qualitative data. Before the main survey, the data collection instruments were pretested with 35 non-sample households to assess their reliability and validity. We then revised and refined the tools based on feedback from this pilot exercise to improve clarity, relevance, and effectiveness. To ensure accurate and contextually appropriate communication, all questionnaires were translated into Amharic, the local language spoken by the target population.

Six enumerators were recruited for data collection based on their prior experience with field surveys and fluency in the local language, ensuring effective communication and data accuracy. They received a single two-day training covering the ODK, ethical standards for data collection, and proper administration of the questionnaires. Data collection was facilitated using the Kobo Collect mobile application, with daily uploads to a centralized Open Networked Analysis (ONA) server to ensure secure and timely data management. Throughout the data collection process, researchers provided continuous support and guidance to the enumerators, addressing any challenges that arose from start to finish.

2.4. Data analysis

We analyzed the collected data using both descriptive and inferential statistical methods. Specifically, we applied Principal Component Analysis (PCA) to estimate the resilience capacity of households. In addition, we employed one-way ANOVA to test whether mean resilience capacity scores varied significantly across the three agroecological zones in the Gubalafto district. This approach aligns with the study's objective of comparing group-level outcomes, as it enables the evaluation of differences in resilience capacity across independent categorical groups (i.e., agroecological zones). The model assumptions were considered in the PCA and ANOVA analyses. For instance (i) normality was tested using a histogram and the Shapiro–Wilk test, and the results indicated that the data were normally distributed; (ii) multicollinearity was test, as covariates were not perfectly correlated with each other, ensuring reliable estimation; this was verified using pairwise correlation (pwcorr) and variance inflation factor (VIF) tests; (iii) identified variables: continuous dependent variable (resilience index) and more than two discrete independent variables, which was identified like lowland, midland, and highland. Measurement error and selection bias were addressed through rigorous enumerator training and pretesting of survey tools to minimize misinterpretation and recording errors. Additionally, Cronbach's alpha was applied to evaluate the internal consistency of items measuring the same construct. These steps helped ensure data reliability and validity.

Measuring resilience is not a straightforward activity, as it is not directly observable. In this study, resilience was treated as a latent variable to be estimated via indicators, which were estimated via observable household-level variables. Bene et al. (2014) Propose that resilience emerges as the result of three capacities: absorptive, adaptive and transformative capacities. In this study, three major dimensions of resilience were identified: (i) absorptive capacity (ABPC), (ii) adaptive capacity (ADPC), and (iii) transformative capacity (TRNC). These three major dimensions were subdivided into subcomponents/indicators. Each of the indicators has constructed from observable variables (Table 1). The resilience capacity index (RCI) was created using these indicators, which can be combined to determine the absorptive, adaptive, and transformative capacities of households. The same procedures were used by (Teklu et al., 2023). To estimate RC*i*, it is necessary to estimate it separately.

$$ABP_j = f(FSSN_j, ISSN_j, DMEWS_j, RM_j),$$
$$ADP_j = f(FC_j, ADPS_j, W_j, FS_j, SE_j, OFF_j), \text{ and}$$
$$TRN_j = f(ITSN_j, INFRA_j, SN_j, SS_j) \quad (3)$$

Where ABP_j is the absorptive capacity of household j, FSSN: formal social safety net, ISSN: informal formal social safety net, DMEWS: disaster mitigation and early warning system RM: risk management, FC: farmer characteristic, ADPS: adaptation strategies, W: wealth, FS: food security, SE: socioeconomic, OFF: off farm IT: information and training, INFRA: use of infrastructure of household, SN: social network, and SS: social service of household j for j = 1. . . n.

The composite household resilience capacity (RCi) was also derived from the set of resilience dimensions, as outlined below.

$$CRi_j = f(ABP_j\ ADP_j, TRN_j) \quad (4)$$

Where CRi_j is the resilience capacity index of household j, and ABP_j is absorptive capacity, ADP_j is adaptive capacity, and TRN_j is transformative capacity of household j for j = 1. . . n.

However, resilience is not directly observable, and we cannot directly estimate the resilience or resilience dimensions. To overcome such challenges, Principal Component Analysis (PCA) was chosen over Factor Analysis (FA) to estimate resilience capacity primarily due to its suitability for data reduction and its minimal reliance on strong statistical assumptions (Alinovi et al., 2008). This study focuses on variance and dimensionality reduction, i.e., simplifying data for further analysis and running with PCA, whereas factor analysis is more suitable for exploring underlying relationships, i.e., the underlying factors influencing resilience capacity. PCA is designed to extract maximum variance from observed variables and summarize them into a smaller set of uncorrelated components. This aligns well with resilience measurement, which often involves diverse indicators that need to be synthesized into a composite index. FA assumes that observed variables are influenced by unobserved latent factors and includes error terms, which may not be appropriate or identifiable in resilience studies with limited sample sizes, whereas FA often requires larger samples and strong assumptions about error structures and latent variables (Jolliffe and Cadima, 2016).

The necessary statistical criteria for a robust PCA model were checked. For instance, the Bartlett Test of Sphericity was conducted via factor test to assure variables significantly correlation with the components or not. Subsequently, KMO was conducted to measure sampling adequacy of individual variables used in the model. Rather, continuous variables were standardized and categorical variables were normalized, while variables with negative implications for resilience were reverse-coded.

The resilience estimation was conducted hierarchically. First, resilience blocks (indicators) were derived from observable household-level variables using Principal Component Analysis (PCA). As proposed by Kaiser (1960), an eigenvalue greater than 1 criterion was applied to select components. In addition, components can also be "rotated" to simplify the structure of the loadings matrix. Implies a varimax rotation technique was used to produce more interpretable component. Varimax rotation is an orthogonal rotation technique applied after PCA to achieve a simpler and more interpretable component structure. It allows each variable to load strongly on only one principal component, making it easier to identify and label the underlying dimensions. Thus, achieving the heaviest loading of principal component expressed in terms of the variables as an index for each household that captured the largest amount of information.

Subsequently, dimensional resilience index for each household was estimated separately using the derived indicators. Indices for each dimension were calculated as the product of the component scores and their corresponding weights (explained variance) (Adane, 2018). Accordingly, the model specified in Equation (3) was transformed into Equation (5). Hence, the dimensional resilience scores (CI_i) for each household was computed as follows:

$$CI\text{i} = \text{w1} \times \text{CS1} + \cdots + \text{wj} \times \text{CSij} \qquad (5)$$

Where CI_i is the score of a dimension (absorptive, adaptive, and transformative), w_j is the percentage of variance explained by the i^{th} component (weight), and CS_{ij} is the component score of the i^{th} household on the j^{th} component.

Following the above argument, this study employed 14 variables to measure households' absorptive capacity, 16 variables to measure their adaptive capacity, and 13 variables to measure their transformative capacity (Table 2).

In the second stage, PCA was applied to the resilience dimension, which was derived from the first-stage exercise. Finally, the resilience capacity index (RCi) was estimated for each household as a product of the component score and weight (explained variation) of a component via Equ 6.

$$\text{RCi} = \frac{\sum_{i=1}^{3} wjCIj}{\sum_{i=1}^{3} wj} \qquad (6)$$

Where RC_i is the composite resilience score, CI_j is component score of j^{th} component, w_j is the weight of the j^{th} component.

The estimated continuous dimensional and composite resilience scores were normalized to a 0–1 scale. These normalized values were then rescaled into three categories: According to the cut-off points proposed by Jayadas and Ambujam (2021) and Siminyu et al. (2020), households' resilience levels were classified as follows: scores between 0.00 and 0.33 indicate low resilience, scores from 0.34 to 0.66 indicate medium resilience**,** and scores from 0.67 to 1.00 indicate high resilience.

Table 2: Overview of the resilience capacity dimensions and indicators

Dimension	Indicators/components	Variables	Literature	Measurement
Absorptive capacity index	Formal and Informal social safety net	Income from PSNP	-	Annual getting in Birr
		Friend support	(Teklu et al., 2022)	Annual getting in Birr
		Informal social insurance	(Teklu et al., 2022)	1 if yes 0=otherwise
		Formal aid (NGO and Gov.)	-	Annual getting in Birr
	Disaster mitigation and early warning system (DMEWS)	Access to weather information	(Teklu et al., 2022)	1 if yes 0=otherwise
		Mobile phone communication	(Teklu et al., 2022)	1 if yes 0=otherwise
		Possession of communication Radios and televisions	(Ali et al., 2023)	1 if yes 0=otherwise
	Risk management	Remittances	(Ali et al., 2023)	Annual getting in Birr
		Decrease th quantity of meal	(Teklu et al., 2022)	1 if yes 0=otherwise
		Decrease diversity of meal	(Teklu et al., 2022)	1 if yes 0=otherwise
		Decrease the number of meal	-	1 if yes 0=otherwise
		Borrow grain from neighbors	(Teklu et al., 2022)	1 if yes 0=otherwise
		Sales of livestock	(Teklu et al., 2022)	Amount in Birr
		Provision of farm Labour	(Siminyu, 2021)	1 if yes 0=otherwise

Dimension	Indicators/components	Variables	Literature	Measurement
Adaptive capacity index	Farmer characteristics	Sex of household head	(Ali et al., 2023)	1 if male 0 female
		Marital status	(Ali et al., 2023)	0 if single, 1 if married, 2 if divorced, 3
		Education level measured in years	(Siminyu, 2021)	0= uneducated, 1=informal educated, 2 =primarily educated, 3 secondary
		Age	(Ali et al., 2023)	Age in years of HH
		Farming experience	(Ali et al., 2023)	experience in year
		Labor availability	(Quandt, 2018)	Number of HH members b/n 18 – 55
	Adaptive strategies	Different crops planted	(Quandt, 2018)	1 if yes 0=otherwise
		Use of improved verities	(Ali et al., 2023)	1 if yes 0=otherwise
		Use of water-harvesting technologies	(Teklu et al., 2022)	1 if yes 0=otherwise
	Wealth and income	Working on-farm	(Siminyu, 2021)	1 if yes 0=otherwise
		Working off-farm	(Siminyu, 2021)	1 if yes 0=otherwise
		Total farm size	(Ali et al., 2023; Teklu et al., 2023)	Farm size in hectare
		Income source/average annual income	(Siminyu, 2021; Teklu et al., 2022)	Average annual income in Birr
		Livestock holding	(Ali et al., 2023)	TLU
		Deposit in bank	(Siminyu, 2021)	Total amount on Birr
		Physical asset	-	Value in Birr
	Food security	Food consumption score	(Getaneh et al., 2022)	poor <=21, borderline if 21.5-35, Acceptable if >35
		Multidimensional food security	(Kini, 2022)	food security if 1, mildly FI if 2, moderately FI if 3, severe FI if 4
Transformative capacity index	Information, Training, and Social Networks	Access to extension service	(Teklu et al., 2022)	1 if yes 0=otherwise
		Access to agricultural training	(Teklu et al., 2022)	1 if yes 0=otherwise
		Membership in iqub	(Ali et al., 2023)	1 if yes 0=otherwise
	Infrastructure	Access to credit	(Quandt, 2018))	1 if yes 0=otherwise
		Access to irrigation	(Ali et al., 2023)	1 if yes 0=otherwise
		Distance to school	(Ali et al., 2023)	Take in hours
		Distance to health	(Quandt, 2018)	Take in hours
		Distance to market	-	Take in hours
		Distance to dirk water	(Ali et al., 2023)	Take in hours
		Reliable all-weather road	(Ali et al., 2023)	1 if yes 0=otherwise
		water and sanitation facilities	(Siminyu, 2021; Teklu et al., 2022)	1 if yes 0=otherwise
		Electricity	(Siminyu, 2021; Teklu et al., 2022)	1 if yes 0=otherwise

Source: (Author`s compilation, 2024)

3. Results and Discussion

3.1. Examining factors contributing to resilience capacity

Absorptive capacity: The size of component loading for each variable has important for policy implications; specifically, higher loadings indicate greater importance and should receive more policy attention. Before estimating absorptive capacity, each household's component scores were indexed (predicted) through PCA. Accordingly, the latent variable (ABPC) score was calculated using (Equ 7), which represents the sum of the principal component scores multiplied by the proportion of variation (weight) explained by each component.

$$ABPCi = pc1 * 0.234 + pc2 * 0.119 + pc3 * 0.102 + pc4 * 0.095 \quad (7)$$

Where: ABPCi = absorptive capacity score for ith household; pc1, pc2 pc3 pc4= component score of the ith household.

Table 3 presents the component loadings of the variables used to estimate absorptive capacity (ABPC). As indicated, four components were retained due to their eigenvalues exceeding one. The Bartlett Test of Sphericity was significant ($\chi 2$=1061.84, p<.0.01), confirming that all fourteen variables were statistically significant, indicating adequate correlation with the components. Subsequently, KMO was 0.705 and well had above 0.5 for individual variables used in the model.

Each variable exhibited loadings greater than 0.3 or less than -0.3, reflecting their substantial contributions to ABPC. Thus, the necessary statistical criteria for a robust PCA model were fulfilled, as outlined by Kaiser's Rule (KMO values above 0.5). As indicated in (Table 3) first, second, third, and fourth components accounted for 23.4%, 11.9%, 10.2%, and 9.5% of the variation, respectively. Together, these variables explain 55.03% of the total variation. The findings revealed that, excluding remittances and formal aid, all other variables were positively and significantly associated with ABPC (p<0.01). This suggests that locally accessible and socially embedded resources, rather than external transfers, are more predictive of households' ability to absorb shocks. Notably, access to weather information, ownership of communication devices (such as radios, TVs, and mobiles), livestock sales, and informal social insurance had strong loadings on the first component, indicating their significant contributions to estimating ABPC. This finding align with Demisse et al. (2024), who found that safety nets and mobile phones are significant contributors to ABPC. Similarly, the importance of productive safety nets, meal reduction strategies, and grain borrowing from neighbors were major contributors to ABPC. This is consistent with Sunday et al. (2023), who found that access to informal safety nets is vital for enhancing the absorptive capacity of rural households in Uganda. This finding infer that access to weather information, communication devices, and informal safety nets is more critical for enhancing households' ability to absorb shocks.

Adaptive capacity: As shown in Table 4, the KMO value was 0.7187, indicating that the sample size was sufficient to conduct PCA. Additionally, Bartlett's test of sphericity was significant (p = 0.01, $\chi 2$= 2138.058), demonstrating significant correlations between each component and the variables. Therefore, the PCA model was deemed satisfactory and was used for estimation. As indicated in (Eq. 8), each household's component scores were indexed (predicted) through PCA. Subsequently, the ABPC score was computed using the component scores and the relative variance explained by each component as weights. Therefore, the ADPC score for each household was calculated as the weighted sum of its scores times the variance of each of the six components.

$$ADPCi = pc1 * 0.23 + pc2 * 0.14 + pc3 * 0.09 + pc4 * 0.08 + pc5 * 0.06 + pc6 * 0.06 \quad (8)$$

Where: ADPCi = adaptive capacity score for ith household; pc1, pc2 pc3 pc4 pc5 pc5= component score of the ith household.

As indicated in (Table 4) six components were extracted to calculate the ADPC scores, based on the criterion of eigenvalues greater than 1, accounting for 67% of the total variance in the model. Subsequently, the components generated were significant in terms of the proportion of total variance explained and both were considered as the underlying ADPC. Notably, the first, second, third, fourth, fifth and sixth components obtained 23.1, 14.3, 9.5, 7.9, 6.2, and 6% of the variation respectively.

Table 3: Component loadings of variables used to estimate the ABPC

Variables	Rotate, varimax			
	Comp1 (Disaster mitigation and early warning system)	Comp2 (Risk-management)	Comp3 (Informal social safety net)	Comp4 (Formal social safety net)
Productive safety net				0.611
Friend support			0.579	
Formal aid (NGO and GO)				-0.69
Remittances		-0.386		
Informal social insurance	0.304			
Access to weather information	0.541			
Mobile phone communication	0.415			
Ownership of radio and TV	0.511			
Decrease quantity of meal			0.331	
Decrease number of meal		0.623		
Decrease diversity of meal		0.6247		
Borrow grain from neighbors			0.533	
Sales of livestock	0.3349			
provision of farm labour			0.361	
proportion of variance	0.234	0.119	0.102	0.095
Total variance explained/Rho: 55.03%				
Scale reliability coefficient/cronbach's alpha: 0.544				
Bartlett Test of Sphericity: Chi-Square=1061.84, p=.000				
KMO Measure of Sampling Adequacy=0.706				

Source: (Authors household survey, 2024)

Except for the sex of the household head, all other variables were strongly and positively correlated with ADPC at p<0.01, indicating their significant contribution to the ADPC. The negative loadings of sex indicate that ADPC decline as the head of household is female. Physical assets, average annual income, and cash savings were grouped together and exhibited their highest component loadings on the first component. Meanwhile, educational level, farming experience, and the age of the household head showed higher loadings on the second component. Annual income, improved seed varieties, and water harvesting technologies were grouped together and exhibited their highest component loadings on the fourth component, indicating that these variables play a significant role in shaping household adaptive capacity. These findings align with evidence from Bekuma (2024), who noted that improved seed varieties and water conservation practices enhance both productivity and resilience among smallholder farmers. Likewise, Negera et al. (2025) reported that income diversification through off-farm employment strengthens adaptive capacity by reducing dependence on rain-fed agriculture and mitigating climate risks.

Table 4: Component loadings of variables used to estimate the adaptive capacity

Variables	Rotate, varimax					
Variables	Comp1 (Wealth and income)	Comp2 (Socio-economic)	Comp3 (Demographic characteristics)	Comp4 (Adaptive strategy)	Comp5 (Food security)	Comp6 (Off farm income)
Sex household head			-0.665			
Marital status			0.666			
Education level of HH		0.463				
Farming experience		0.601				
Labor availability						0.399
Age of household head		0.601				
Different crops planted	0.386					
Improved verities				0.363		
Water harvesting technologies				0.329		
Working none-farm	0.307					
Working off-farm						0.839
Physical asset	0.4547					
Average annual income	0.401			0.601		
Cash saving	0.449					
Multidimensional food security					0.777	
Food consumption score				0.514		
proportion of variance	0.231	0.143	0.05	0.079	0.062	0.061
Total variance explained/Rho: 67%						
Scale reliability coefficient/alpha: 0.704						
Bartlett Test of Sphericity: Chi-Square= 2138.058, p=.000						
Kaiser-Meyer-Olkin Measure of Sampling Adequacy: 0.719						

Source: (Authors household survey, 2024)

Transformative capacity: Transformative capacity is the third latent variable of resilience capacity, which enables conditions that foster resilience. Before estimating transformative capacity (TRNC), each household's component scores were indexed (predicted) through PCA. Subsequently, TRNC was calculated based on the component scores and the relative variance explained by each component as weights. The TRNC score for each household was derived as the weighted sum of its scores multiplied by the variance of each of the six components (Equ. 9).

$$TRNC_i = pc1 * 0.308 + pc2 * 0.154 + pc3 * 0.126 + pc4 * 0.077 \quad (9)$$

All statistical requirements for a valid PCA model were tested and met, consistent with the Kaiser criterion. Specifically, the sample size was sufficient to run PCA, as indicated by the KMO measure (0.7827) and Bartlett's sphericity test, which was significant ($p < 0.01$, $\chi2 = 1617.5$). In estimating transformative capacity, 13 observed variables were included in the PCA model. Four independent components were retained for calculating the TRNC scores based on an eigenvalue greater than 1. Together, these variables explain 66.5% of the total variation

As presented in (Table 5) all thirteen variables were found to be positive and statistically significant, with component loadings greater than 0.358. The positive and high loadings of these variables indicate their significant contribution to estimating transformative capacity. Specifically, access to extension services, agricultural training, all-weather roads, and electricity, as well as the distance to the nearest school, health institution, and market, had strong loadings, indicating that each significantly contributes to the estimation of transformative capacity. This finding aligns with (Asmamaw et al., 2019; Dessie and Demsie, 2024).

Table 5: Component loadings for the variables used to estimate the TRNC

	Rotate, varimax			
Variables	Comp1 (Training, information and basic services	Comp2 (Infrastructure)	Comp3 (Social network)	Comp4 (Social services)
Access to extension				0.676
Access to agricultural training				0.537
Membership in iqub		0.495		
Membership RUSACO		0.609		
Access to credit		0.586		
Access to irrigation				0.409
Distance to nearest school	0.581			
Distance to nearest market	0.555			
Distance to nearest health institution	0.594			
Distance to drink water			0.489	
All-weather road			0.509	
Clear drink water and sanitation			0.358	
Electricity			0.588	
proportion of variance	0.308	0.154	0.126	0.077
Total variance explained/Rho: 66.5%				
Scale reliability coefficient/alpha: 0.746				
Bartlett Test of Sphericity (chi-Square= 1617.5,P =.000				
Kaiser-Meyer-Olkin Measure of Sampling Adequacy: 0.783				

Source: (Authors household survey, 2024)

Composite resilience capacity: As presented in the methodology section, PCA was conducted in its second stage to calculate the overall resilience capacity index (RCI) using the results from the three dimensions of resilience capacity. As a result, the Bartlett Test of Sphericity was significant ($p<0.01$, $\chi2=60.076$), indicating sufficient correlations among the variables and their corresponding components. The KMO measure of sampling adequacy was 0.59. Therefore, all statistical criteria for the goodness of fit of the principal component analysis model were met.

As indicated (Table 6) following the Kaiser criterion, one component was retained as its eigenvalue was equal to or greater than one, accounting for approximately 50% of the total variance. The component loadings for absorptive, adaptive and transformative capacity were 0.612, 0.534, and 0.583, respectively, indicating that absorptive capacity is a key contributor to enhancing resilience in rural households. This finding is align with work in Somalia by and in Ethiopia by Martin (2019) who reported that absorptive capacity had the highest component loadings and largest contribution to household resilience. But, the research conducted by Dessie and Demsie (2024) reported that transformative capacity is pivotal in influencing household resilience. Also, studies conducted in Tanzania and Uganda by Asmamaw et al. (2019), which revealed that adaptive capacity is the primary contributor to enhancing resilience capacity. Also, studies conducted in Tanzania and Uganda by d'Errico et al. (2018), which revealed that adaptive capacity is the primary contributor to enhancing resilience capacity. In contrary, d'Errico et al. (2018) also reported a negative correlation between transformative capacity and household resilience, suggesting that structural factors may not uniformly translate into improved outcomes without complementary enabling conditions. Overall, this finding suggests that absorptive capacity is the most critical factor for overall household resilience in rural households, significantly enhancing their ability to respond to shocks and stresses.

.

Table 6: Component loadings of resilience capacity to climate change

Dimensions	Rotate, varimax Comp1 (composite resilience capacity)
Absorptive capacity	0.612
Adaptive capacity	0.534
Transformative capacity	0.583
Variance: 0.4841	
Total variance explained/Rho: 0.4841	
Scale reliability coefficient/alpha: 0.4091	
Bartlett Test of Sphericity: Chi-Square= 50.44, p=.000	
Kaiser-Meyer-Olkin Measure of Sampling Adequacy:0.591	

Source: (Author household survey, 2024)

3.2. Household resilience capacity status

This paper used a resilience capacity index (RCI) as a proxy measurement of household climate resilience capacity. It generated household dimensional resilience indices and composite RCI. First, the absorptive capacity (ABPC), adaptive capacity (ADPC), and transformative capacity (TRNC) were estimated using fourteen; sixteen, and thirteen variables, respectively.

As indicated in (Figure 2), approximately 19% of rural households were found to be high resilience capacity. This proportion is moderately consistent with findings by Ali et al. (2023) , who reported that

12.23% of households exhibited high resilience. Meanwhile, 44% of households in the current study fell into the low resilience category, suggesting that nearly half may be vulnerable to climate-related shocks. It is consistence with (Wereta et al., 2025).

Also, this vulnerability pattern aligns with Atara et al. (2020), who found that 61% of households in the Sidama zone were classified as non-resilient. The remaining 38% of households in Gubalafto demonstrated medium resilience capacity. This distribution contrasts slightly with Siminyu et al. (2020), whose study in a similar East African setting revealed that most households had resilience indices ranging between 0.34 and 0.66, indicating a predominance of medium resilience. Suggesting divergence in resilience profiles across these studies may reflect differences in livelihood strategies, institutional support, and agro-ecological conditions. This study finding highlights persistent resilience gaps in rural communities, underscoring the need for targeted, context-specific interventions to strengthen resilience capacity and reduce vulnerability.

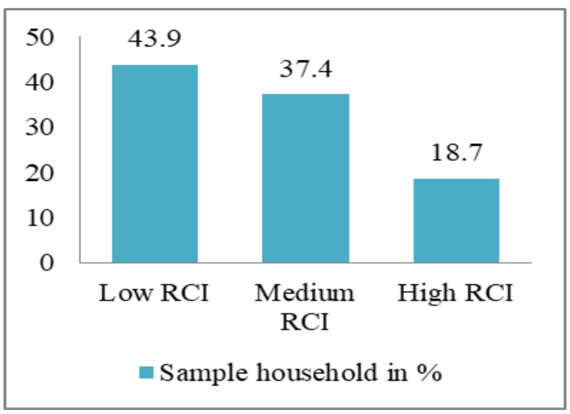

Figure 2: Resilience status of households

As indicated in (Figure 3), highland and midland areas account for approximately 37% of households with low resilience followed by lowland zones (27.1%). This pattern underscores the pronounced vulnerability of highland and midland households, which not only represent the largest share of the sample but also exhibit the highest concentration of low resilience. Suggests lowland communities may benefit from more favorable conditions such as access to irrigation, remittances, and lower erosion rates that enhance their adaptive capacity. In contrast, Tofu et al. (2023b) reported that in the Mekiet district, midland households exhibited higher resilience due to diversified farming systems and improved access to agricultural services, while lowland households were more vulnerable. On the other hands, this study findings are broadly consistent with the work of Jayadas and Ambujam (2021), Aboye et al. (2023), and DEEP (2025), both were confirm resilience variations across agroecological zones. Critically, the results from this study underscore the importance of agroecological context in shaping household resilience outcomes. The overall findings revealed varying degrees of resilience capacity across agro-ecological zones.

3.3. Agroecological-wise of resilience capacity

The resilience index for each agroecology offers a nuanced understanding of how different areas cope with challenges. As described in Joerin et al. (2014), this approach allows to better visualize resilience across agroecological contexts. To do so, one-way ANOVA was employed to test mean difference of household resilience capacity among the different agroecological zones.

As shown in (Table 7), the mean of ABPC, ADPC, and TRNC were 0.466, 0.320, and 0.239 respectively. This indicated that the mean ABPC is greater than the others. A statistically significant mean difference in ABPC was observed between agroecology with a significance level of 0.0147. Surprisingly, the mean ABPCI in the highland was 0.485, exceeding the values of the other two agroecology zones. On the contrary, the midland agroecology had a mean index of 0.422, which was lower than those of the highland and lowland.

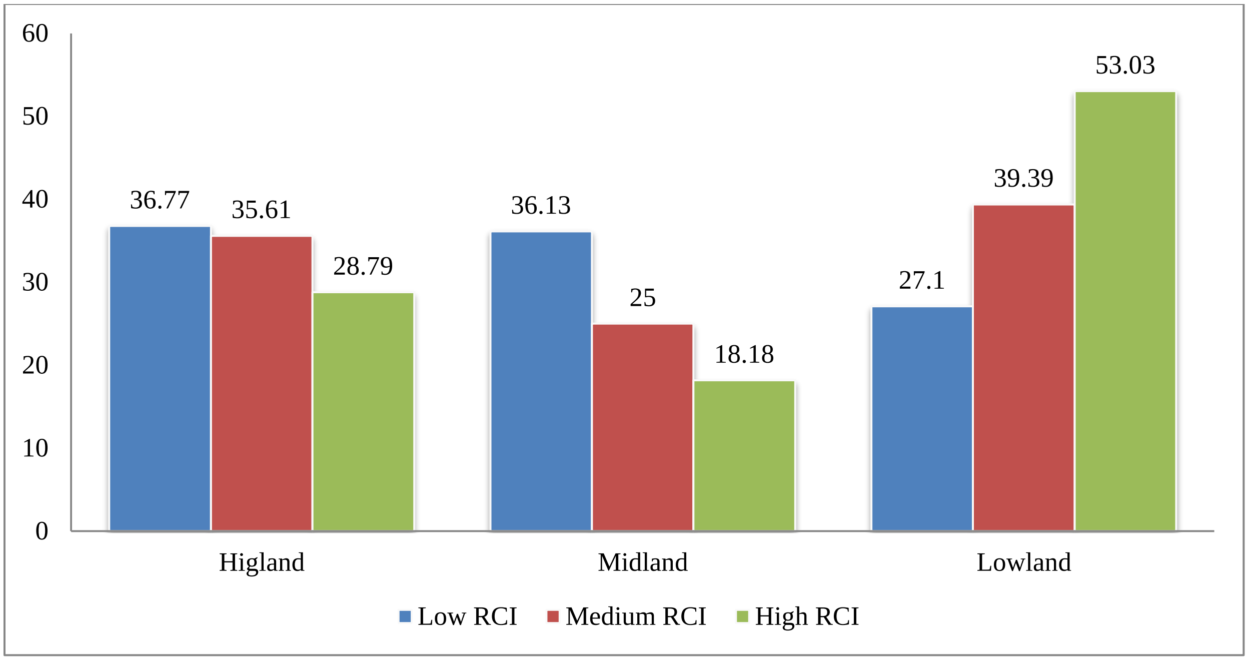

Figure 3: Resilience index distribution of households in precent

RCI = Resilience capacity

Another plausible interpretation is that the mean ABPC in the midland was 0.061 units lower than highland, with a significance level of 0.032. This indicates that midland's mean ABPC was approximately 6.1% times lower than highland. Similarly, there was a mean difference of 0.059 in ABPC between lowland and midland, with a significance level of 0.041. This means that the mean ABPC of lowland is 5.9% times higher than the dega, suggesting that the mean ABPC in lowland is higher than in midland (see Table 8). As observed that many farmers in midland lack access to government aid and the Productive Safety Net Program (PSNP) compared to those in highland, which may contribute to the lower absorptive capacity in midland. Additionally, farmers in midland had limited access to remittances compared to those in lowland.

There was a statistically significant difference in ADPC scores between the three agroecology, with a significance level of 0.0318. The average ADPC score was highest in lowland (0.339); followed closely by highland (0.332), while midland records the lowest mean at 0.282 (see Table 7). Table 8 further confirms that difference in mean ADPC between lowland and midland was 0.057, with a significance level of 0.041. This means that ADPC of lowland was 0.057 times higher than the mean ADPC of midland. This suggests that the conditions in lowland may lead to better ADPC outcomes compared to midland.

Table 7: One-way ANOVA: Resilience status of agroecological zones

Agro-ecology	Absorptive capacity	Transformative capacity	Resilience capacity
Highland	0.485	0.208	0.307
Midland	0.422	0.23	0.253
Lowland	0.481	0.277	0.416
Mean	0.466	0.239	0.331
Std. dev.	0.179	0.208	0.323
Prob > F	0.0147	0.0272	0.0004

Source: (Authors household survey, 2024)

A one-way ANOVA was conducted to assess mean differences in resilience indices across agroecological zones, revealing an overall mean RCI of 0.33 (Table 8). Surprisingly, lowland had the highest mean RCI (0.416), followed by highland (0.307), and while midland had lowest mean RCI (0.253). This result indicated a significant mean difference among the agroecology zones, with a p-value of 0.01. Specifically, lowland had a statistically significant higher mean RCI compared to highland, with a p-value of 0.02, showing a difference of 0.039 in mean RCI. Similarly, lowland was higher than by 0.042 mean RCI as compared to highland. This is in line with (Tofu et al., 2023a), who reported that the resilience index for lowlands is 0.328, demonstrating that lowland agro-pastoral livelihoods are comparatively better adapted to climate variability. This study confirm that there are varying degrees of resilience across different agro-ecological. This finding aligns with previous research by Atara et al. (2020), which indicated that various livelihood systems contributed significantly to variations in household resilience capacity. Thu, underlining the critical role of geographic contexts in shaping household resilience capacities is so important.

Table 8: Multiple comparisons of marginal linear prediction

Absorptive capacity	Contrast	Std. dev.	P>|t|
Midland vs. highland	-0.061	0.024	0.032**
Lowland vs. highland	-0.003	0.022	1.00
Lowland vs. midland	0.059	0.024	0.041**
Adaptive capacity			
Midland vs. highland	-0.049	0.023	0.104
Lowland vs. highland	0.008	0.022	1.00
Lowland vs. midland	0.057	0.023	0.041**
Transformative capacity			
Midland vs. highland	0.022	0.028	1.00
Lowland vs. highland	0.046	0.028	0.276
Lowland vs. midland	0.069	0.026	0.026**
Resilience capacity index			
Midland vs. highland	-0.053	0.042	0.628
Lowland vs. highland	0.109	0.039	0.02**
Lowland vs. midland	0.162	0.042	0.00***

Source: (Authors household survey, 2024)

4. Conclusion and Recommendation

Absorptive capacity plays a critical role in building household resilience capacity, followed by adaptive and transformative capacities. Absorptive capacity showed relatively better performance, suggesting some households demonstrating the ability to cope with immediate shocks. Significant proportion of rural households exhibited low resilience, indicating majority of households lack the ability to adapt and transform their practices in response to climate change.

Highland and midland areas showed higher concentrations of low resilience, while lowland households demonstrated relatively stronger resilience, likely due to better access to irrigation, remittances, and reduced erosion.

Policy makers should enhance adaptive and absorptive capacities through tailored extension services, early warning systems, and climate-smart infrastructure. In addition, targeting agroecological vulnerabilities by prioritizing interventions in highland and midland zones where resilience is lowest.

The authors recognize the inherent limitations of using cross-sectional data which leads the possibility of bias in data collection, particularly in addressing potential endogeneity concerns. Reliance on self-reported data for yields and income may be subject to recall bias, potentially affecting the accuracy of the resilience assessment. To enhance validity, future research should triangulate these findings with extension records where available and investigate long-term resilience using longitudinal data.

Acknowledgments

The authors acknowledge Gubalafto Woreda Administration, Agricultural, Irrigation offices for their financial support. They also extends their acknowledgment to Bahir Dar and Woldiya Universities.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript.

Data Availability Statement

Data will be made available on request.

Funding

This study was funded by the Ministry of Education of Ethiopia.

References

Aboye, A., Kinsella, J., and Mega, T. (2023). Farm households' adaptive strategies in response to climate change in lowlands of southern Ethiopia. *International Journal of Climate Change Strategies and Management*, *15*. https://doi.org/10.1108/IJCCSM-05-2023-0064

Adane, A. (2018). *Rural households' resilience to food insecurity in Southern Ethiopia: The case of Boricha Woreda in Sidama Zone* Phd Thesis. Ethiopia: Addis Ababa University].

Ali, H., Menza, M., Hagos, F., and Haileslassie, A. (2023). Impact of climate smart agriculture on households' resilience and vulnerability: An example from Central Rift Valley, Ethiopia. *Climate Resilience and Sustainability*, *2*(2), e254.

Alinovi, L., Mane, E., and Romano, D. (2008). Towards the measurement of household resilience to food insecurity: applying a model to Palestinian household data. In *Deriving food security information from national household budget surveys. Experiences, achievement, challenges* (pp. 137-152). Food and Agricultural Organization of the United Nations.

Andualem, T. (2016). A review on cattle husbandry practices in Ethiopia. *International Journal of Livestock Production,*, *7*(2), 5-11. https://doi.org/ https://doi10.5897/IJLP2015.0276

Antwi-Agyei, P., Dougill, A. J., Fraser, E. D., and Stringer, L. C. (2013). Characterising the nature of household vulnerability to climate variability: Empirical evidence from two regions of Ghana. *Environment, Development and Sustainability*, *15*, 903-926.

Asmamaw, M., Mereta, S. T., and 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.

Asnake, B., and Elias, E. (2017). Challenges and extents of soil and water conservation measures in Guba-Lafto Woreda of North Wollo, Ethiopia. *Journal of Agricultural Research and*

Development, *7*(2), 103-110. https://doi.org/https://doi.org/10.18685/EJARD(7)2_EJARD-16-012

Atara, A., Tolossa, D., and 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.

Ayugi, B., Eresanya, E. O., Onyango, A. O., Ogou, F. K., Okoro, E. C., Okoye, C. O., Anoruo, C. M., Dike, V. N., Ashiru, O. R., and Daramola, M. T. (2022). Review of meteorological drought in Africa: historical trends, impacts, mitigation measures, and prospects. *Pure and Applied Geophysics*, *179*(4), 1365-1386.

Bahta, Y. T., and Myeki, V. A. (2022). The impact of agricultural drought on smallholder livestock farmers: Empirical evidence insights from Northern Cape, South Africa. *Agriculture*, *12*(4), 442.

Bekuma, G. M. (2024). Climate-Smart Agriculture and Agricultural Diversification Effects on Productivity and Resilience of Smallholder Farmers in Ethiopia. *International Journal of Energy and Environmental Science*, *9*(6), 130-142.

Belay, A., Recha, J. W., Woldeamanuel, T., and Morton, J. F. (2017). Smallholder farmers' adaptation to climate change and determinants of their adaptation decisions in the Central Rift Valley of Ethiopia. *Agriculture and Food Security*, *6*(1), 1-13. https://doi.org/https://doi10.1186/s40066-017-0100-1

Bene, C., Newsham, A., Davies, M., Ulrichs, M., and Godfrey-Wood, R. (2014). Resilience, poverty and development. *Journal of international development*, *26*(5), 598-623.

Béné, C., Newsham, A., Davies, M., Ulrichs, M., and Godfrey-Wood, R. (2014). Resilience, poverty and development. *Journal of international development*, *26*(5), 598-623.

Bene, C., Wood, R. G., Newsham, A., and Davies, M. (2012). Resilience: new utopia or new tyranny? Reflection about the potentials and limits of the concept of resilience in relation to vulnerability reduction programmes. *IDS Working Papers*, *2012*(405), 1-61.

Cochran, W. G. (1963). *Sampling Techniques (2nd ed.)*. John Wiley and Sons.

d'Errico, M., Romano, D., and Pietrelli, R. (2018). Household resilience to food insecurity: Evidence from Tanzania and Uganda. *Food Security*, *10*(4), 1033-1054.

DEEP. (2025). *Resilience to CliIDate Change in Ethiopia (2021-2025): Tracking Changes and Unpacking Intra-Household Responses Third Survey Report*. https://doi.org/10.55158/DEEPRP1

Demisse, U., Bazezew, A., and Bantigegen, S. (2024). Rural households' resilience to the adverse impacts of climate variability and food insecurity in the North-eastern highlands of Ethiopia. *Heliyon*, *10*(12).

Dessie, T. A., and Demsie, B. S. (2024). Rural household resilience to food insecurity in Mekiet district, Ethiopia. *Frontiers in Sustainable Food Systems*, *8*, 1391904.

Ethiopian Ministry of Agriculture (MoA). (2022). *Agroecology: An Extension Training Manual*. https://moa.gov.et/wp-content/uploads/2025/01/20220325_Agroecology-Manual.pdf

Ethiopian Statistical Service. (2022). *Ethiopia Population Projection 2022*. https://data.reqiq.co/data/ethiopia-population-projection-2022/

Fadairo, O., Olajuyigbe, S., Osayomi, T., Adelakun, O., Olaniyan, O., Olutegbe, N., and Adeleke, O. (2020). Climate Change, Rural Livelihoods and Ecosystem Nexus: Forest Communities in Agro-ecological zones of Nigeria. In (pp. 1-24). https://doi.org/10.1007/978-3-030-42091-8_155-1

Frankenberger, T., and Nelson, S. (2013). Background paper for the expert consultation on resilience measurement for food security. *TANGO International–Expert Consultation on Resilience Measurement Related to Food Security, sponsored by the Food and Agricultural Organization and World Food Programme, Rome, Italy, February*, 19-21.

Gilbert, N., and Stoneman, P. (2015). *Researching social life*. Sage.

Green, F. E. s. C. R. (2019). Economy National Adaptation Plan. *FDRE: Addis Ababa, Ethiopia*.

Harvey, C. A., Saborio-Rodríguez, M., Martinez-Rodríguez, M. R., Viguera, B., Chain-Guadarrama, A., Vignola, R., and Alpizar, F. (2018). Climate change impacts and adaptation among smallholder farmers in Central America. *Agriculture and Food Security*, *7*(1), 1-20.

IPCC. (2021). *Climate change 2021: The physical science basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.*

Jayadas, A., and Ambujam, N. (2021). Research and design of a Farmer Resilience Index in coastal farming communities of Tamil Nadu, India. *Journal of Water and Climate Change*, *12*(7), 3143-3158.

Jiri, O., Phophi, M. M., Mafongoya, P. L., and Mudaniso, B. (2022). Climate change adaptation and resilience on small-scale farmers. In *Disaster Risk Reduction for Resilience: Disaster and Social Aspects* (pp. 451-462). Springer.

Joerin, J., Shaw, R., Takeuchi, Y., and Krishnamurthy, R. (2014). The adoption of a climate disaster resilience index in Chennai, India. *Disasters*, *38*(3), 540-561.

Jolliffe, I. T., and Cadima, J. (2016). Principal component analysis: a review and recent developments. *Philosophical transactions of the royal society A: Mathematical, Physical and Engineering Sciences*, *374*(2065), 20150202.

Kaiser, H. F. (1960). The application of electronic computers to factor analysis. *Educational and psychological measurement*, *20*(1), 141-151. https://doi.org/https://doi.org/10.1177/00131644 6002000

Koo, J., Thurlow, J., ElDidi, H., Ringler, C., and De Pinto, A. (2019). *Building resilience to climate shocks in Ethiopia*. International Food Policy Research Institute.

Kosmowski, F. (2018). Soil water management practices (terraces) helped to mitigate the 2015 drought in Ethiopia. *Agricultural water management*, *204*, 11-16.

Martin, S. (2019). Somalia resilience recurrent monitoring survey (RMS) report. *February*. *The Resilience Evaluation, Analysis and Learning (REAL) Associate Award, Washington, DC*.

Mekonnen, A., Tessema, A., Ganewo, Z., and Haile, A. (2021). Climate change impacts on household food security and farmers adaptation strategies. *Journal of Agriculture and Food Research*, *6*, 100197.

Mengistie, D., and Kidane, D. (2016). Assessment of the impact of small-scale irrigation on household livelihood improvement at Gubalafto District, North Wollo, Ethiopia. *Agriculture*, *6*(3), 27. https://doi.org/ https://doi.org/10.3390/agriculture6030027

Negera, M., Dejen, Z. A., Melaku, D., Tegegne, D., Adamseged, M. E., and Haileslassie, A. (2025). Agricultural productivity of solar pump and water harvesting irrigation technologies and their impacts on smallholder farmers' income and food security: evidence from Ethiopia. *Sustainability*, *17*(4), 1486.

Nguyen, H. L., and Akerkar, R. (2020). Modelling, measuring, and visualising community resilience: A systematic review. *Sustainability*, *12*(19), 7896.

Oxfam. (2017). *The Future is a Choice Absorb, adapt, transform Resilience Capacities*.

Shi, Y., Zhao, L., Zhao, X., Lan, H., and Teng, H. (2022). The Integrated Impact of Drought on Crop Yield and Farmers ' Livelihood in Semi-Arid Rural Areas in China. *Land*, 1-13. https://doi.org/https://doi.org/10.3390/land11122 260

Siminyu, P. (2021). Assessing the contribution of climate-smart agricultural Assessing the contribution of climate-smart agricultural practices to the resilience of maize farmers in Bungoma County, Kenya Philip. *Agricultural and Resource Economics* *16*(2), 126-139. http://ageconsearch.umn.edu

Siminyu, P., Mbau, J., and Oluoch-Kosura, W. (2020). The contribution of climate smart agriculture practices in mitigating farmers against maize yield losses, a case of Bukembe ward in Bungoma county. *Journal of Sustainability, Environment and Peace*, *3*(2), 41-45.

Sunday, N., Kahunde, R., Atwine, B., Adelaja, A., and George, J. (2023). How specific resilience pillars mitigate the impact of drought on food security: Evidence from Uganda. *Food security*, *15*(1), 111-131.

Tefera, W. (2021). *Determinants of Rural Households' Resilience Capacity to the Effect of*

Land Degradation: The Case of Gubalafto Woreda,

Teklu, A., Simane, B., and Bezabih, M. (2022). Effectiveness of Climate-Smart Agriculture Innovations in Smallholder Agriculture System in Ethiopia. *Sustainability (Switzerland)*, *14*(23). https://doi.org/ https://doi.org/10.3390/

Teklu, A., Simane, B., and Bezabih, M. (2023). Effect of Climate Smart Agriculture Innovations on Climate Resilience among Smallholder Farmers: Empirical Evidence from the Choke Mountain Watershed of the Blue Nile Highlands of Ethiopia. *Sustainability (Switzerland)*, *15*(5), 1-26. https://doi.org/ https://doi.org/10.3390/su15054331

Tofu, D. A., Fana, C., Dilbato, T., Dirbaba, N. B., and Tesso, G. (2023a). Pastoralists' and agro-pastoralists' livelihood resilience to climate change-induced risks in the Borana zone, south Ethiopia: Using resilience index measurement approach. *Pastoralism*, *13*(1), 1-14.

Tofu, D. A., Mekuria, M. M., and Ogato, G. S. (2023b). Climatic extremes' resilient livelihoods of rural households in the Eastern Ethiopia. *Agriculture and Food Security*, *12*(1), 42. https://doi.org/10.1186/s40066-023-00446-0

Walker, B., and Salt, D. (2012). *Resilience thinking: sustaining ecosystems and people in a changing world*. Island press.

Wereta, M. S., Ayele, Z. A., and Damtie, Y. A. (2025). A review on climate-smart agriculture technologies and its impacts on small-scale farmers' livelihood in Ethiopia. *Journal of Water and Climate change*, *16*(6), 1913-1926.

WFP and CSSA. (2022). *Comprehensive Food Security and Vulnerability Analysis (CFSVA)*, .

Yamane, T. (1967). Statistics: An introductory analysis.

KoThari, C. (2004). Research Methodology-Methods and Techniques.