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Research article

Agricultural livelihood resilience in the face of recurring droughts: Empirical evidence from northeast Ethiopia

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ABSTRACT

The main purpose of this study was to characterize the livelihood resilience of smallholder farmers in the face of recurring droughts in northeast Ethiopia. The data was collected using a cross-sectional survey of 274 households and five focus group discussions. Principal component analysis and multiple linear regression models were employed to analyze the data. The Livelihood Resilience Index (LRI), framed on absorptive, adaptive, and transformative capacities, was used to quantify the households' livelihood resilience. The results indicated that about 57% of the surveyed respondents were non-resilient, while 43% were resilient to different degrees. Abay Tekeze watershed (ATW) livelihood zone exhibits the highest proportion of resilient households (57.4%), while North Wollo highland *belg* has the lowest proportion (22.7%). The high resilience in ATW was attributed to the relatively lower persistence of droughts, better accessibility in enabling institutions, more access to agricultural inputs, and the training and support given to farmers. The better-off were more resilient (90.9%) than the medium (52.1%) and the poor (34.6%) households. Among the latent dimensions, sensitivity with β value −0.372, climate change and variability (−0.33), and enabling institutions and environments (0.288) showed a significant ($p < 0.0001$) influence on LRI. This was followed by adaptive capacity and food access (0.249), agricultural practice and technology (0.213), and asset possession (0.19), in respective order. It implies that the absorptive capacity of households showed the leading influence in determining LRI, while adaptive and transformative capacities had nearly similar low effects. Thus, it is recommended that future planning for building livelihood resilience and drought risk interventions in the area should address the levels of resilience identified and the relative importance of each latent dimension indicated.

1. Introduction

Around the world, disasters and other emergencies are becoming more critical health, socio-economic, and development challenges [1]. Natural and man-made disasters have increased in frequency during the last few decades. Human influences are increasingly the root cause or exacerbating the effects of recurring disasters [2]. The majority of disasters are characterized by immediate shocks that destroy people, livelihoods, infrastructure, and institutions [3]. However, some others, like droughts, are complex and slowly encroaching hazards that spread over a larger geographical area [4]. In recent decades, drought has become more recurrent and severe across the globe [5]. With climate change, droughts are expected to increase in severity, frequency, duration, and spatial extent,

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making the impacts more intense [6].

Although drought occurs throughout the world, its recurrence and associated effects are not as frequent and severe as they are in Africa, notably in Ethiopia [7]. Ethiopia is extremely vulnerable to drought, with greater than a 40% annual probability of moderate to severe droughts during the rainy season [8]. As a result, drought has been the country's most significant disaster over time. According to Mekonen and Berlie [9], water stress and droughts have become more common in Ethiopia as a result of a combination of predicted climate change, rapid population growth, limited agricultural land availability and cultivation of marginal lands, land over-exploitation, and a lack of proper soil and water conservation techniques. Between 1950 and 2017, 34 droughts hit the different parts of Ethiopia, revealing that meteorological droughts, which propagated into other types, broke out every two years [10]. Some of the droughts were short-lived and ended in less than a year, while others lingered for three years or longer. In addition, most droughts are often followed by devastating famines and starvation [11]. Consequently, drought in Ethiopia has affected almost all regions, including previously drought-free areas. However, the northeastern, southeastern, eastern, and rift valley areas were those affected more frequently than the others [10].

In Ethiopia, drought has persistently caused profound and widespread socio-economic and environmental consequences. It is known to cause more deaths, disrupt resources, and force more people to displace from their homes than any other natural disaster [12]. However, the highest (about 84%) damage and losses caused by droughts occur in the agriculture sector [13]. It is because agriculture and farmers are much more sensitive to any climate extremes, given their strong dependence on weather-sensitive natural resources [11,14]. Such consequences are responsible for Ethiopia's most extensive loss of agricultural production [15]. This has been a major contributor to the growing impoverishment of communities and households (HHs), resulting in chronic and severe food insecurity [16]. The impact of droughts on agricultural livelihoods is thus a combination of the weather itself and people's resilience capacity to sustain and improve their livelihood opportunities and well-being, notwithstanding the biophysical, socio-economic, and political disturbances [17].

Resilience is a relatively new concept in disaster risk management. It is a metric that indicates a system's ability to recover from failure and resume normal functioning [3,18]. According to the United Nations office of Disaster Risk Reduction (UNDRR) [1] report, "the difficulty of determining the onset and end of droughts; the complex, slow, and creeping nature of their impacts; the site dependence of the impacts; and the diffuse nature of associated damages" seriously deteriorate environmental sustainability. In doing so, the ability of the region to withstand, survive, and recover from a drought hazard has a lot to do with how a region and its ecosystem is capable of withstanding, surviving, and recovering from a drought [19]. Therefore, studying the resilience can be a good way to assess how well a region is prepared for drought. This concept highlights the ways to reduce hardship and the vulnerability of drought risk-prone communities within a practical framework of building resilience [3]. Unlike vulnerability, resilience seeks ways to reduce the adverse effects of a hazard instead of resisting it by focusing on activities taken during and after the hazard [20].

Resilience has become an essential operational concept in places where people are chronically vulnerable or food insecure [21]. Despite the increased interest in promoting resilience, there is currently no consensus on how this construct can be defined, much less how it should be measured [22]. However, since interventions aimed at increasing resilience in different dimensions continue to grow, there is now an urgent need to tackle the problem of assessing resilience [23]. With the purpose of delivering reliable, data-driven insights into the characteristics, capacities, and processes observed at various scales (individual, household, community, and system/state), data from resilience measurements will aid in evaluating the effectiveness of interventions and informing discussions on how to build resilience [24]. Therefore, studying resilience (livelihood resilience to drought in this case) can be an excellent way to assess how the farming HHs, including the agricultural system are prepared for drought impacts. It also helps to highlight the means of reducing the intended hardship [18]. Generally, the livelihood resilience analysis in the face of drought helps to obtain a complete understanding of the risk and vulnerability of the subjects [25].

Although the recurrence of droughts and associated impacts are found to be the greatest challenge to livelihood security in the Ethiopian population, few studies on drought resilience have been conducted. Most resilience studies in Ethiopia [7,26,27] were concentrated on household or community resilience to climate change and variability on a regional or national scale. Others, like Daie and Woldtsadik [28] and Weldegebriel and Amphune [29], were concentrated on livelihood resilience in the face of recurring floods. To the best of the author's knowledge, there have been few studies specifically focused on the livelihood resilience of smallholder farmers to drought and associated impacts. The prominent example is Birhanu et al. [30], who assessed the resilience of Borena pastoralists to the impacts of recurrent droughts through a context-specific and data-driven resilience framework.

However, insights into livelihood resilience to climate extremes (drought in this case) significantly vary with the scale of analysis [7]. Livelihood resilience to drought-induced shocks assessed at national and regional levels can obscure variations in the local resilience of HHs. Accordingly, the previous studies' macro-scale (national and regional level) assessments could have overlooked variations in households' resilience capacity at the local (district) level. Because at the district level, the farming HHs might differ in levels of food insecurity, level of income, educational status, coping strategies and adaptive capacity, access to credits, public services, safety nets, local exposure, and natural resource utilization [31], to mention but a few. The present study was conducted based on these premises to better understand the livelihood resilience of the farming households to drought-induced shocks in northeast Ethiopia, particularly North Wollo. Hence, this study aims to quantify and characterize the livelihood resilience of smallholder farmers in the face of recurring droughts. It targets HHs and ranks them according to their resilience capacity (the likelihood of resisting a shock) at a specific moment in time. The information obtained helps to identify the target, apply appropriate adaptation strategies, take mitigation measures, facilitate relief interventions, and build future resilience.

2. Materials and methods

2.1. Study setting

The study was conducted in the North Wollo Zone, which is part of the northeast highlands of Ethiopia (Fig. 1). It is situated between 11° 20′ N to 12° 34′ N and 38° 25′ E to 39° 57′ E, having a total area of 12,179.6 km^2 [32]. The area is dominated by rugged topography with steep slopes and mountainous areas not suitable for agriculture. Altitude of the area ranges from 968 to 4258 m.a.s.l [16]. In terms of agro-ecology, lowland (*Kolla*), mid-latitude (*Woina-dega*), Highland (*Dega*), and Cold (*Wurch)* covers about 38, 34, 21, and 7% area of the zone, respectively [32]. Most of the area is inaccessible owing to lack of all-weather roads and rugged topography.

The overall population of the zone was estimated to be 1,824,361 in 2017, with 913,572 males and 910,789 females. From these over 85.2% of the population are rural residents [33]. Based on the temperature and rainfall data of the area (1992–2019), the average annual mean maximum temperature of the highland area reaches to 20.6 °C, while lowlands are with a 30.4 °C. The annual mean minimum temperature extends from 7.1 °C to 15.4 °C in the cool and warm drier parts of the zone, respectively. The area receives a total annual rainfall of 1061.2 mm in the *woina-dega* and 624.8 mm in the drier parts of the *Kolla* agro-ecologies (Analysis of data from national meteorology agency).

Mixed crop-livestock production system is the base of livelihoods for farming households in the area. There are four main livelihood zones in the area namely, north Wollo east plain (NWEP), northeast *woina-dega* mixed cereal (NEWMC), Abay Tekeze watershed (ATW), and North Wollo highland *belg* (NWHB), covering 32.6, 25.3, 29.4, and 11.4% of the zone, respectively. Besides, in 1.3% of the zone's total area there is also a true pastoral livelihood zone bordering the Afar. The shape file for the livelihood zonation is documented and freely available from https://fews.net/east-africa/ethiopia/livelihood-zone-map/january-2018.

2.2. Sampling and data source

The target population for this study is the farming HHs living in different livelihood zones and respective agro-ecologies of the study area. The primary data was obtained from a household questionnaire survey. The structured questionnaire, which include multiple-response, open-ended, and dichotomous questions were designed to address all the indicators organized for the livelihood resilience analysis. Five *woredas* were purposely selected from different agro-ecologies and livelihood zones. Five rural *kebele* administrations were selected contingent on the area coverage of the livelihood zones using a simple random technique. Stratified random sampling was employed to determine the respondents. Accordingly, samples in each kebeleconsidered the three wealth groups (better-off, medium, and poor), which the Woreda's agriculture office already determined and later revised by the focus group discussions (FGDs).

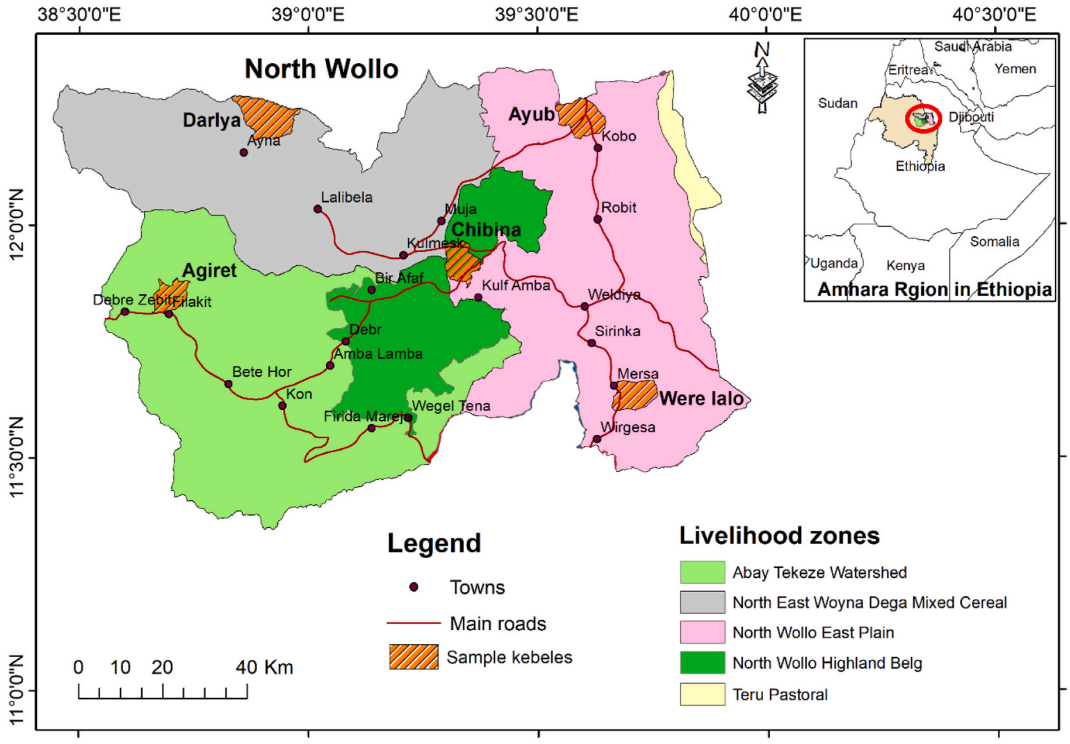

Fig. 1. Map of the study area.

Using the formula developed by Ref. [34], a total of 274 sample size was selected from the aggregated 7754 HHs of the specified *kebeles,* in the survey year 2020. Since the number of better-off, medium, and poor differs from *kebele* to *kebele,* probability proportionate to size was used to fix the sample size in each. Hence, from 638 better-offs, 2050 medium, and 5066 poor wealth groups, 22, 73, and 179 household samples were considered, respectively.

Finally, since this manuscript includes experimentation on human subjects, it was first approved by the ethical approval committee at the faculty level that all the experiments and other processes conducted were according to the established ethical guidelines, and the informed consent obtained from all the participants during the data collection, focus group discussion, key informant interview and other related activities.

2.3. Method of analysis

2.3.1. Identification of indicators

Indicators of resilience are nested within each other and come together in diverse configurations to define the resilience of a particular household's livelihood's [35]. The first step was the identification of the six pillars of livelihood resilience. Based on the Resilience Index Measurement and Analysis (RIMA) model of FAO (2012), with subsequent contextualization, eight major indicators (pillars) such as asset possession (AP), agricultural practice and technology (APT), climate change and variability (CCV), enabling institutions and environments (EIE), sensitivity (S), and adaptive capacity and food access (ACFA) were identified.

The transition from a conceptual to an analytical framework of resilience necessitates the definition and identification of the most precise indicators for each pillar. One could be based on a theoretical understanding of relationships, and the other could be based on statistical relationships. In addition, an extensive review of existing literature with subsequent customized profiles and hypothesized functional relationships, as well as discussions with experts in the field, was conducted to select the appropriate indicators for each pillar. Initially, therefore, about six resilience indicators categorized under the three resilience capacities, having a total of 52 sub-indicators, were prepared (Fig. 2). As applied by Alinovi et al. [37] and Ado et al. [38], the multi-stage modeling with some modification below showed the path diagram of the household resilience.

2.3.2. Estimation of livelihood resilience

There is currently no agreement on how to quantify resilience [22,39]. Identifying metrics and standards for measuring resilience remains a big challenge, which is unsurprising [27,40]. One of the reasons for making it challenging to measure resilience and vulnerability is that we can only determine if a system or a HH in it has successfully coped or adapted after a disaster or drought shock [41]. In other words, we must wait until after the shock or change has occurred before evaluating the success of the intervention in question. The serendipitous convergence of these two principles has resulted in an overwhelming number of frameworks for evaluating, assessing, and comprehending resilience [42].

Birhanu et al. [30] argued that resilience and its dimensions might vary across contexts and need to be carefully developed and adjusted to the specific local context and constellation of dimensions in each community. Based on all the preceding discussions, it is evident that calculating resilience via a proxy variable technique is the most straightforward option [29]. Since resilience is a multifaceted concept, however, difficulty in identifying indicators/variables that will work as proxies for livelihood resilience is considered the approach's limitation. In addition, it is also challenging to find the determinants of resilience. As a result, the multi-stage modeling technique proposed by Alinovi et al. [37] was found appropriate as it promotes flexibility to adapt to different real-life cases. The implementation of this technique was based on the assumption that the options available to a household to make a living would determine the household's resilience at a given point in time.

Therefore, FAO's RIMA-I model [36], which was later improved into RIMA-II [43], was used as a basis to measure the livelihood

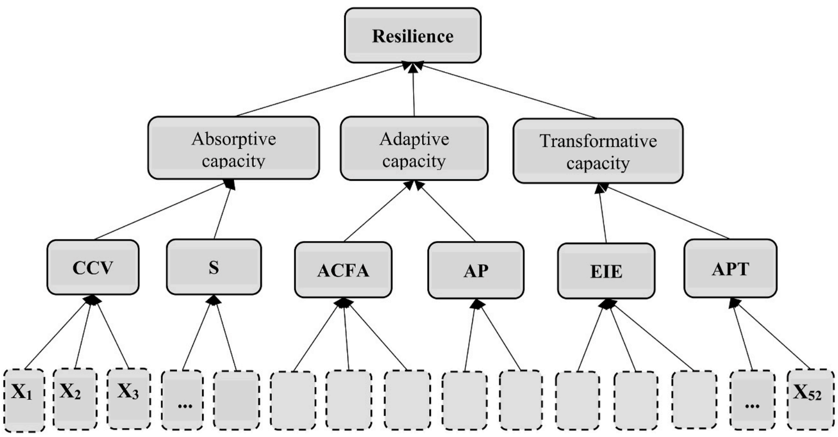

Fig. 2. Path diagram of the household resilience model. The broken boxes represent observed variables, while the solid boxes refers to the latent variables.

resilience index (LRI) of HHs in the study area. The model has been applied to measure a household's resilience to food insecurity. The RIMA model was also used for household resilience analysis to climate change-induced shocks (droughts, floods), food insecurity, and livelihoods with contextualization, in various studies like Asmamaw et al. [26], Mekuyie et al. [7], Weldegebriel and Amphune [29], and Daie and Woldtsadik [28]. Based on the model with subsequent contextualization, LRI in the present study is a function of six variables (eq. (1)).

$$\boldsymbol{LRI}_i = \boldsymbol{f}\ (\boldsymbol{AP}_i, \boldsymbol{APT}_i, \boldsymbol{ACFA}_i, \boldsymbol{EIE}_i, \boldsymbol{S}_i, \boldsymbol{CCV}_i) \tag{1}$$

where, LRI_i = Livelihood resilience index of ith household; AP = Assets possssion; APT = Agricultural practice and technology; CCV = Climate change & variability; EIE = Enabling institution and environments; S = Sensitivity; ACFA = Adaptive capacity and food access.

CCV = climate change and variability; VHI; vegetation health index; HHs = households; NGOs = non-governmental organizations; DAs = development agents; SWC = soil and water conservation.

As this index is a rough approximation of resilience and scale-sensitive, which may not be helpful for inter-household comparison, a composite index using PCA [44] was applied. PCA is a multivariate statistical method of data reduction that condenses a large number of variables into a smaller number of spatially explicit, potentially incommensurable variables called principal components (PCs) while preserving as much information as possible [45]. So, PCA in this study was used both for data reduction and the identification of dominant factors (PCs) that better explain households' livelihood resilience to drought impacts.

Prior to starting the analysis, we employed the Kaiser-Maier-Olkin (KMO) sampling adequacy measure and Bartlett's sphericity tests to see if all of the variables stored in the dataset of 274 HHs could be factored for the PCA or not. According to the suggestion of Jolliffe [46], the sample size and the proportion of variance in variables that underlying factors might cause are adequate for running PCA when KMO >0.5. Besides, Bartlett's sphericity test is used to test the null hypothesis that the original correlation matrix is an identity matrix in which all correlation coefficients (R-matrix) would be zero, showing that the variables are unrelated. Consequently, smaller values of significance level ($p < 0.05$) are required to suggest a well-fit variable with nearly an identity matrix. According to Kaiser's criteria, the cutoff for appropriate components lies on PCs with eigenvalues greater than one [46]. This rule of thumb was applied to select the appropriate factor and further scoring methods. Thus, the individual resilience score of each HH was computed using the PCA as per equation (2).

$$\boldsymbol{LRS}_i = [\boldsymbol{f}_1(\boldsymbol{a}_{i1} - \boldsymbol{m}_1) / \boldsymbol{S}_1 + \boldsymbol{f}_2(\boldsymbol{a}_{i2} - \boldsymbol{m}_2) / \boldsymbol{S}_2 + \ldots + \boldsymbol{f}_n(\boldsymbol{a}_{iN} - \boldsymbol{m}_N) / \boldsymbol{S}_n]\boldsymbol{F}_N \tag{2}$$

where, LRS_i = the livelihood resilience score for the latent variable in ith household; f_1, f_2, f_N = the component loading generated by PCA for each factor or variable; a_{i1} = the ith household's value for the first variable; m1, S1 = the mean and standard deviation of respectively of the first variable over the HHs; F_N = the number of factors.

However, when adopting a multivariate technique, it is essential to use a relevant approach and methods while generating factor scores [28]. Among the Thompson's regression, Anderson-Rubin's, and Bartlett's approaches of generating factor scores, the impact of shared (common) factors on factor scores is better demonstrated using Bartlett's scoring approach, which ensures that the resulting factor scores are significantly associated with their respective factors. It generates unbiased estimates of the actual factor scores since it uses maximum likelihood estimations, an estimate that most likely represents the "true" factor scores, which is the advantage over the other two [47]. As applied by Daie and Woldtsadik [28], Bartlett's approach was, therefore, used, in this study, to choose the variables and generate latent dimensions that later used as variables for the overall livelihood resilience index estimation of each household.

Each household's overall livelihood resilience index (LRI) was computed using equation (3). It was computed by applying the same PCA model, using the previously estimated six latent variable scores saved in the SPSS active data set. In this case, however, it was found to be unwise to remove some latent variables that provide independent information compared to others. Hence, as suggested by Jolliffe [46], to make total variance explained reach the range of 70%–90%, a sensible cut-off criterion of an eigenvalue ≥0.7 was used for extracting factors. Then, the weighted sum of the generated factors was used to compute the LRI.

$$\mathrm{LRI_n} = \partial 1\ \mathrm{F1} + \partial 2\ \mathrm{F2} + \partial 3\ \mathrm{F3} + \ldots + \partial \mathrm{n}\ \mathrm{Fn} \tag{3}$$

where, LRI_n = the livelihood resilience index of the nth household, ∂n is the variance explained by F1, F2, F3… Fn (the factors generated by the PCA representing each latent dimension).

Finally, after the LRI computation was completed, the relative importance of the latent dimensions in determining the households' livelihood resilience was examined by applying a multiple linear regression analysis using the ordinary least squares (OLS) regression (eq. (4)). The households' LRI scores were used as a dependent variable and the six latent variables as independent (explanatory) variables. This gives the effects of a variable on LRI, given that the other predictors are constant in terms of unstandardized coefficient (B). The rank ordering of the predictors (latent dimensions) in terms of their relative importance or contribution is identified using the standardized (β) coefficient. During the analysis, tests of normality of residuals, overfitting, and multicollinearity diagnosis between the variables have been checked. The empirical model used to predict households' livelihood resilience is expressed as:

$$\mathrm{LRI} = \partial + \mathrm{B_1} \times \mathrm{CCV} + \mathrm{B_2} \times \mathrm{S} + \mathrm{B_3} \times \mathrm{ACFA} + \mathrm{B_4} \times \mathrm{AP} + \mathrm{B_5} \times \mathrm{EIE} + \mathrm{B_6} \times \mathrm{APT} + \varepsilon \tag{4}$$

Where, LRI = livelihood resilience of HHs; ∂ = a constant; B_{1-6} = unstandardized B coefficients of each variable; CCV, S, ACFA, EIE & APT = the six latent dimensions; Ɛ = an error term representing the negligible information of the variables used to estimate resilience.

Table 1
Measurement units and hypothesized relationships of resilience capacities, major indicators, and sub-indicators.

Resilience capacity	Major indicator	Sub-indicator	Measurement or Level of scoring	Hypothesized functional relationship between the sub-indicator & resilience
Absorptive capacity	1. Climate change & variability	• Informed about CCV • Late onset & early cessation of rainfall • Drought occurrence • Extent of extreme events • Build water-harvesting scheme • Preparation to resist future drought • Erratic rainfall • Hail storm occurrence • Extreme cold occurrence	Yes 1; 0 otherwise No 1; 0 otherwise Count drought frequency (VHI) 2000–2009, if < 3 = 2, 3–5 = 1 & >5 = 0 Increased, No = 1; 0 otherwise Yes 1; 0 otherwise Very high = 3; High = 2; less = 1; Not ready yet = 0 Impact imposed: Very high = 0; high = 1; medium = 2; less = 3; very less = 4	Unwelcomed rain affects agricultural activities and decrease resilience; The better HHs are informed about CC and the more they are ready to take remedial action the better they are resilient to drought impacts: persistence of extreme events decrease resilience; repeated occurrence of erratic rainfall, hailstorm & extreme cold reduce farmers' resilience
	2. Sensitivity	• Early warning information • Crop & livestock disease • Pest & Crop weeds • Soil erosion • SWC practice • Fragmented farm plot • Rent in land • Scarcity of livestock fodder	Obtain, Yes 1; 0 otherwise Relative susceptibility of HHs livelihood in relation to effects Not a problem = 4; Less = 3; moderate = 2; Serious = 1 & very serious = 0 Yes 1; 0 otherwise Number <3 parcels Yes 1; No = 0 Yes 1; 0 otherwise Not a problem, Yes 1; 0 otherwise	The higher the prevalence the greater the damage and the lower the resilience; Increased soil erosion decrease productivity and decrease resilience; fragmented farmlands consume labor & time & make farmers less resilient; engagement in SWC increase HHs resilience
Adaptive capacity	3. Adaptive capacity & food access	• Sex of HH head • Family size • Family productive age group • Farm experience • Educational level • Number of crops grown • Number of livelihood activities • Access to credit • Food self-sufficiency • Number of months in a year facing no food deficit	Male headed HH, Yes 1; 0 No Size of a family (continuous) Age within 15–64 ≥ dependent age (age <15 & 64+): Yes 1; 0 No Experience in years (continuous) Illiterate 0; read and write = 1; grade 1–4 = 2 grade 5 & above = 3 Type of crops harvested (2019) For >1 livelihood activities yes 1; 0 otherwise Get access: Yes 1; 0 otherwise Yes 1; 0 otherwise Number of months (continuous)	Being male, with larger family size and more productive age group possibly increase HH livelihood resilience; Higher literacy rate increase resilience; Harvesting different crops & diversifying livelihoods reduce vulnerability & improve resilience: more credit access help HHs easily pass adverse conditions & be resilient HHs with better food self-sufficiency can more healthy and highly resilient
	4. Asset possession	• Farm size • Livestock owned (TLU) • Off-farm income • Non-farm income • Remittance as income source • Saving accounts • Radio or TV ownership	Size in *timad* (continuous) TLU in 2019 (continuous) Eth. Birr per year (2019) Eth. Birr per year (2019) Yes 1; 0 otherwise Possess: yes 1; 0 otherwise Yes 1; 0 otherwise	The higher the percentage of HHs with asset ownership, and access to these income sources the lesser the vulnerability and the more resilient they are

Resilience capacity	Major indicator	Sub-indicator	Measurement/Level of scoring	Hypothesized functional relationship between the indicator & resilience
Transformative capacity	5. Enabling institution & Environment	• Member & participation in *Idir* • Member & participation *Iqub*	Yes 1; 0 otherwise Yes 1; 0 otherwise Yes 1; 0 otherwise Yes 1; 0 otherwise Living <4 kms away: Yes 1; 0 otherwise	The more HHs actively involved in *Idir, Iqub, mekanajo & Debbo* the bitter their resilience will be; The higher the % of HHs living <4 kms, from market & all-weather roads raise their resilience; access to clinic improve health of farmers & decrease livelihood vulnerability; more support and training improve resilience

(*continued on next page*)

Table 1 (*continued*)

Resilience capacity	Major indicator	Sub-indicator	Measurement/Level of scoring	Hypothesized functional relationship between the indicator & resilience
		• Participation in Wenfel/ Debbo • Participation *Mekenajo* • Distance to market • All weather road • Access to clinic • Access to veterinary service • Advise & follow-up by DAs • Access to social safety net	Available in *kbele*: Yes 1; 0 otherwise Yes 1; 0 otherwise Yes 1; 0 otherwise	Getting access to social safety net improve farmers resilience
Transformativ capacity	6. Agricultural practice & technology	• Access to irrigation • Application of improved seeds • Application of chemical fertilizer • Application of compost • Application of herbicides • Application of pesticide • Obtain training & support • Preparedness to apply all remedial action & technology	Yes 1; 0 otherwise Yes 1; 0 otherwise Yes 1; 0 otherwise Yes 1; 0 otherwise Yes 1; 0 otherwise Yes 1; 0 otherwise Yes 1; 0 otherwise Yes 1; 0 otherwise	Access to irrigation make farms easily cop with and adapt to weather shocks; Application of farm inputs minimize farmers vulnerability and maximize their adaptive capacity to drought and other climate-induced impacts; obtaining training and support improve farmers resilience

3. Results

Based on the results of different statistical tests applied to verify the PCA and select the prioritized factors for each latent dimensions, the KMO value was 0.683 and a significant Bartlett's sphericity test (at p = 0.000 and Chi-square = 5406.772). Hence, the model was fitted for running the PCA. The PCA was run for each resilience capacities and collectively yields 18 distinct and reliable factors prioritized based on the rule of thumb cut-off eigenvalues (>1).

3.1. Estimation of latent indicators of household livelihood resilience

3.1.1. Absorptive capacity

Absorptive/reactive capacity is the ability to minimize or avoid exposure shocks (drought-related) and stresses through appropriate preventative measures and other coping strategies [48]. It depends on the ability of the individual farming household to prevent and prepare for the drought-related shocks before they cause negative impacts. Thus, about seventeen sub-indicators were prepared under the two dimensions (CCV and S) and analyzed separately.

3.1.1.1. Climate change and variability (CCV). Exposure to the environmental system is determined by changes in climatic conditions,

Table 2
Communalities, factor loadings and correlations of the CCV sub-indicators.

Sub-indicators of CCV	*Communalities*		*Factor and their loads*			*Correlation to CCV*
	Initial	Extraction	1	2	3	
Build a water-harvesting scheme	1.000	.584	.586	.066	.088	0.598**
Hailstorm occurrence	1.000	.580	.592	−.060	−.134	0.376**
Drought occurrence	1.000	.545	.160	.608	−.081	0.539**
Erratic rainfall	1.000	.581	−.014	.482	.409	0.594**
Extent of extreme events	1.000	.782	−.027	−.143	.823	0.369**
Informed about CCV	1.000	.430	.263	−.496	.529	−0.008
Eigenvalues	Total		1.297	1.181	1.023	
	Variance (%)		21.615	19.687	17.053	
	Commutative (%)		21.615	41.302	58.355	

KMO test of sampling adequacy = 0.510
Bartlett's test of sphericity is significant at p = 0.010; Approx. Chi-square = 30.468
Extraction Method: Principal Component Analysis.
**correlation is significant at the 0.01 level (2-tailed)

seasonal variations in temperature and rainfall amount, and associated extreme events such as droughts [49]. A highly affected environment hurts agricultural activities, affecting the farming community's livelihood and resilience capacities [26]. Hence, CCV is one of the most important dimensions that need to be considered in examining the households' livelihood resilience in this study.

After running relevant multivariate analysis using available sub-indicators designed to measure the influence of the CCV, pertinent variables were selected based on the factor loadings, communalities, and variance explained. Initially, nine observed variables were included in the PCA analysis (Table 1), where three sub-indicators were excluded in the process since they have cross-loadings. Table 2 shows that the measure of sampling adequacy (KMO) is 0.51, and Bartlett's sphericity test is significant (at $p = 0.01$, Chi-squared = 30.468). These results indicate that the samples are adequate for this factor analysis.

It can be observed that the communalities and initial commonalities before rotation are all above 0.3, which tells us the proportion of variation in each measured sub-indicator share with the retained components, which is an acceptable measure. Then, based on the eigenvalue, three independent factors were retained in the PCA for the CCV latent variable. These three factors together explained 58.4% of the overall variation. In each of the retained factors, two sub-indicators were heavily loaded (shaded in grey color) so that the respective components largely represent those sub-indicators.

The relative size of each variable's factor loading has substantial policy implications. The higher the load, the more critical it is and the greater the policy focus should be. Generally, the factor scores from the three factors can be utilized to estimate the CCV score since the suggested statistical requirements all fit. As a result, using the proportion of variance explained by each factor as a multiplying coefficient, the latent variable (CCV) score was estimated using equation (5), which was further used as an input variable to compute the overall livelihood resilience of each household.

$$CCV = [(0.21615 * F1) + (0.19687 * F2) + (0.17053 * F3)] / 3 \tag{5}$$

where, CCV = livelihood resilience score in climate change and variability block; F1, F1 &.F3 = factor loadings.

3.1.1.2. Sensitivity (S). Farmers in most parts of Ethiopia, and the study area in particular, rely on small-scale mixed crops and livestock to support their livelihoods. Accordingly, smallholder farmers are extremely susceptible to the biophysical environment and the agricultural system [11]. In this regard, eight sub-indicators were included to measure a household's sensitivity as one latent variable to measure the livelihood resilience index. As depicted in Table 3, the measure of KMO (0.528) and Bartlett's sphericity test (significant at $p = 0.000$, Chi-squared = 61.426) indicate that the sample is adequate for this PCA.

The communalities and initial commonalities (above 0.3) showed an acceptable measure of sensitivity. Using the eigenvalue (>1), three independent factors were retained in the PCA to generate the sensitivity scores. The three factors together explain about 61% of the overall variation. In each retained factor, two sub-indicators are heavily loaded (shaded in grey) so that the respective components largely represented those sub-indicators.where, S = Sensitivity score; F1, F1 & F3 = factor loadings.

3.1.2. Adaptive capacity

Adaptive capacity is an important dimension of a household's ability to adapt and respond to drought shocks. Having more adaptive capacity implies more probability for the HHs to properly mitigate drought impacts [37] that advances livelihood security. The selected sub-indicators under adaptive capacity and food access (ACFA), and asset possession (AP) were used to estimate the adaptive capacity score.

Table 3
Communalities, factor loadings and correlations of the sensitivity sub-indicators.

$$S = [(0.24872 * F1) + (0.19142 * F2) + (0.16996 * F3)] / 3 \tag{6}$$

Sub-indicators of sensitivity	*Communalities*		*Factor and their loads*			*Correlation to S*
	Initial	Extraction	1	2	3	
Early warning information	1.000	.587	.553	.074	.065	0.666**
Implement SWC practice	1.000	.621	.620	−.096	−.095	0.491**
Soil erosion	1.000	.521	−.077	.571	−.217	0.279**
Crop and livestock disease	1.000	.648	.129	.546	.108	0.666**
Scarcity of livestock fodder	1.000	.665	.129	−.267	.734	0.351**
Pest and crop weeds	1.000	.619	−.233	.288	.580	0.365**
Eigenvalues	Total		1.492	1.148	1.020	
	Variance (%)		24.872	19.142	16.996	
	Commutative (%)		24.872	44.013	61.009	

KMO test of sampling adequacy = 0.528
Bartlett's test of sphericity is significant at p = 0.000; Approx. Chi-square = 61.426
Extraction Method: Principal Component Analysis
**correlation is significant at the 0.01 level (2-tailed)

The factor scores from the three defined factors were used to estimate the sensitivity score by applying Bartlett's scoring technique in the PCA. Consequently, the latent variable scores for sensitivity were estimated using equation (6), which was used as an input variable to compute the overall livelihood resilience index.

3.1.2.1. Adaptive capacity and food access (ACFA). A total of ten observed variables were included in determining the ACFA score of HHs to drought-related shocks. Based on the eigenvalue obtained, three independent factors that entirely explain 72.1% of the total variation were retained in the PCA (Table 4). Two sub-indicators were heavily loaded into each retained factor in accordance with the component score loadings obtained by Bartlett's scoring method. So, the respective factors better refer to those sub-indicators than the others. Four sub-components were excluded in the process since they have cross-loadings.

As observed in Table 4, the KMO test, Bartlett's test of sphericity, communalities, eigenvalues, and the total variance explained, were met, permitting to use the factor scores of the three factors to estimate the ACFA score of adaptive capacity. Hence, ACFA was estimated using equation (7), where the result was further employed to compute the overall resilience index.

$$\mathrm{ACFA} = [(0.30203 * \mathrm{F1}) + (0.2348 * \mathrm{F2}) + (0.18406 * \mathrm{F3})] / 3 \tag{7}$$

where, ACFA = resilience score of adaptive capacity and food access; F1, F1⋯F3 = factor loadings.

Five of the six sub-indicators showed a positive, significant ($p < 0.01$) correlation with ACFA, where the first two having strong association with it (Table 4). Access to credit services has a week association with ACFA as compared to the others. According to the FGD discussants, the fundamental reason is that many farmers who participate and get credit access were the poor and the medium rather than the better-offs. Hence, they have a relatively lower adaptive capacity and access to food.

3.1.2.2. Asset possession (AP). Assets are one of the essential elements of household resilience [50]. The more assets HHs possess, the more they can easily withstand drought-induced shocks and the better their resilience will be. As a result, assets should be considered a key factor in the assessment of resilience [7].

Seven observed variables were used to estimate the AP component that this study considered necessary for agro-based livelihood resilience analysis of household's to drought impacts. Three variables were reduced to make the PCA fit with the intended criteria. The sub-indicators such as having saving accounts, radio or TV ownership, remittance, and farm size were then used to generate two factors (Table 5).

As observed from Table 5, the first and second factor together have 63.812% of the total variation. The KMO and Bartlett's sphericity tests are satisfactory to use the factor score generated to compute the AP score (eq. (8)).

$$\mathrm{AP} = [(0.37705 * \mathrm{F1}) + (0.26107 * \mathrm{F2})] / 2 \tag{8}$$

Where, AP = resilience score of asset possession; F1 & F2 = factor loadings.

3.1.3. Transformative capacity

As the highest level of the adaptation process, transformative capacity is a transitional response and change where a household's linkages with and access to external resources and institutions are subsequently measured [29]. In most cases, where the frequency and magnitude of climatic extremes are growing year to year, even though a change is required, it still overwhelms the households' or systems' capacity to adapt. In this case, transformation is necessarily required to ensure resilience by altering an individual or community's primary structure and function. According to Boka [27], transformative capacity of resilience refers to the ability to turn risks into opportunities through technological innovations, institutional reforms, behavioral shifts, and cultural changes, which frequently entails questioning values, challenging assumptions, and the ability to examine fixed beliefs, identities, and stereotypes. Therefore, it underscores the ability of the farming HHs to create a new system to make drought-induced conditions attainable. In this regard, to analyze the livelihood resilience score of the transformative capacity, 18 sub-indicators grouped under EIE, including the social safety net indicator and APT, were separately used in the PCA.

3.1.3.1. Enabling institution and environment (EIE). Many formal institutions, such as banking and insurance, credit and saving associations, and cooperatives, and the informal ones such as *Idir, Iqub, wonfel,* and *mkenajo,* together with the accessibility of markets,

Table 4
Communalities, factor loadings and correlations of the ACFA sub-indicators.

Sub-indicators of ACFA	*Communalities*		*Factor and their loads*			*Correlation to ACFA*
	Initial	Extraction	1	2	3	
Food self-sufficiency	1.000	.852	.510	−.001	−.052	0.649**
No of months with no food shortage	1.000	.853	.511	−.055	.031	0.650**
Male headed HHs	1.000	.684	.019	.639	.171	0.550**
Family size	1.000	.624	−.066	.567	−.107	0.262**
No of crops grown	1.000	.710	.099	.160	.691	0.556**
Access to credit service	1.000	.602	.136	.117	.565	0.005
Eigenvalues	Total		1.812	1.409	1.104	
	Variance (%)		30.203	23.480	18.406	
	Commutative (%)		30.203	53.682	72.088	

KMO test of sampling adequacy = 0.511
Bartlett's test of sphericity is significant at p = 0.000; Approx. Chi-square = 278.705
Extraction Method: Principal Component Analysis.
**correlation is significant at $P < 0.01$ level (2-tailed)

Table 5
Communalities, factor loadings and correlations of the asset possession sub-indicators.

Sub-indicators of AP	*Communalities*		*Factor & their loads*		*Correlation to AP*
	Initial	Extraction	1	2	
Have saving accounts	1.000	.669	.523	−.185	0.535**
Radio or TV ownership	1.000	.642	.529	.096	0.706**
Remittances	1.000	.764	−.119	.813	0.325**
Farm size in *timad*	1.000	.478	.309	.502	0.671**
Eigenvalues	Total		1.508	1.044	
	Variance (%)		37.705	26.107	
	Commutative (%)		37.705	63.812	

KMO test of sampling adequacy = 0.530
Bartlett's test of sphericity is significant at p = 0.000; Chi-square = 64.114
Extraction Method: Principal Component Analysis.
**correlation is significant at the p < 0.01 level (2-tailed)

roads, clinics, and veterinary services, are decisive factors in determining the livelihood resilience capacity of the farming HHs. The assumption is that households use the more these indicators, the more socially integrated they become and the higher their resilience to shocks will be [28].

From the ten sub-indicators of EIE initially used in the PCA, only one was excluded due to the cross-loadings it has within the rotated component matrix. The KMO (0.601) and Bartlett's test of sphericity (significant at $p = 0.000$ and Chi-square = 587.312) were sufficient to proceed with the PCA. Based on the extraction criteria applied and the eigenvalue cut-off, four factors were retained in the analysis that entirely explain 68.958% of the total variation (Table 6). Among them, the first factor captures three sub-indicators (shaded in grey), while the remaining factors capture two sub-indicators each. The component score loadings produced by Bartlett's scoring method were used to name each retained factor as discussed above.

Although they vary in strength, all the sub-indicators revealed a positive significant ($p < 0.01$) association with EIE except for one. However, in the present study, 'Distance to market' showed a very weak negative association ($r = -0.014$) with EIE showing that it has a feeble influence in determining their resilience to drought-induced shocks. Hence, access to institutions and basic infrastructure is crucial in improving farmers' resilience by making easy access to farm inputs, public services, information, and market exchange and creating opportunities for livelihood diversification [37,51]. Finally, the scores of the four factors were used to estimate the resilience score of EIE as indicated in equation (9). The result is then used as one of the latent variables to calculate the overall LRI of each household.

$$EIE = [(0.29050 * F1) + (0.15445 * F2) + (0.12799 * F3) + (0.11664 * F4)] / 4 \tag{9}$$

where, EIE = resilience score enabling institution and environment; F1, F2⋯F4 = factor loadings.

3.1.3.2. Agricultural practice and technology (APT). As listed in Table 1, information about agricultural practices and technology was collected based on the eight sub-indicators. When used in the PCA, one was excluded due to cross-loadings. The KMO value was satisfactory, and Bartlett's test of sphericity was significant (Table 7), permitting us to proceed with the analysis. The initial and extraction communalities were also above 0.3, so factoring could be made possible. Based on the eigenvalue, three factors were retained. The first three sub-indicators were captured by factor 1, having 33.596% of the total variation, the next two by factor 2, and

Table 6
Communalities, factor loadings and correlations of the EIE sub-indicators.

Sub-indicators of EIE	*Communalities*		*Factor and their loads*				*Correlation to EIE*
	Initial	Extraction	1	2	3	4	
Access to clinic	1.000	.862	.477	−.136	.146	.047	0.778**
Access to veterinary service	1.000	.864	.440	−.019	.085	−.014	0.788**
Advice & follow-up from DAs	1.000	.557	.280	−.003	−.167	−.152	0.408**
Member & participation in *Idir*	1.000	.754	−.104	.596	.049	.145	0.491**
Participate in *Wonfel/Debbo*	1.000	.764	−.052	.601	−.048	−.172	0.414**
Distance to market	1.000	.589	−.005	.009	.471	−.143	−0.014
All-weather roads	1.000	.744	.114	.001	.622	.115	0.348**
Member & participation in *Iqub*	1.000	.527	−.027	.006	.138	.662	0.319**
Participation in safety net program	1.000	.546	−.057	−.042	−.175	.624	0.156**
Eigenvalues	Total		2.614	1.390	1.152	1.050	
	Variance (%)		29.050	15.445	12.799	11.664	
	Commutative (%)		29.050	44.495	57.294	68.958	

KMO test of sampling adequacy = 0.601
Bartlett's test of sphericity is significant at p = 0.000; Approx. Chi-square = 587.312
Extraction Method: Principal Component Analysis.
**correlation is significant at the 0.01 level (2-tailed)

Table 7
Communalities, factor loadings and correlations of the APT sub-indicators.

Sub-indicators of APT	*Communalities*		*Factor and their loads*			*Correlation to APT*
	Initial	Extraction	1	2	3	
Access to irrigation	1.000	.570	.342	−.239	.210	0.440**
Application of herbicide	1.000	.699	.463	.057	−.020	0.717**
Application of pesticide	1.000	.668	.472	.120	−.217	0.593**
Application of improved seeds	1.000	.800	.096	.534	−.084	0.678**
Application of compost	1.000	.802	−.077	.548	−.087	0.442**
Training and support	1.000	.831	−.056	−.157	.611	0.390**
Preparedness to apply all remedial action & technology	1.000	.756	−.027	.022	.480	0.501**
Eigenvalues	Total		2.352	1.742	1.032	
	Variance (%)		33.596	24.886	14.749	
	Commutative (%)		33.596	58.483	73.231	

KMO test of sampling adequacy = 0.599
Bartlett's test of sphericity is significant at $p = 0.000$; Approx. Chi-square = 488.499
Extraction Method: Principal Component Analysis.
**correlation is significant at $p < 0.01$ (2-tailed)

the remaining two by factor 3. All three factors showed about 73.231% of the variation, sufficient to compute the factor loadings.

In the end, the factor scores of the three factors were used to estimate the resilience score of APT, as shown in equation (10). The result is again used in the six latent variables to compute the overall LRI of the households.

$$APT = [(0.33596 * F1) + (0.24886 * F2) + (0.14749 * F3)] / 3 \tag{10}$$

where, APT = resilience score of agricultural practice and technology; F1, F2 & F3 = factor loadings.

All the seven sub-indicators have a positive correlation with APT and are all significant at $p < 0.01$ (Table 7). Among them, application of herbicide ($r = 0.717$) and application of improved seeds ($r = 0.678$) showed a strong correlation with the latent variable. In contrast, training and support ($r = 0.39$) relatively exhibited the weakest association.

3.2. The overall livelihood resilience index (LRI)

The PCA model used to compute the overall livelihood resilience index (LRI) for each household showed that four factors were generated, accounting for about 84.718% of the total variance (Table 8). The KMO statistic was 0.621, and Bartlett's test of sphericity was significant (at $p = 0.000$ with Chi-square = 262.241). Factor one (CCV & S) and factor two (EIE & APT) captured two latent variables each. The remaining AP and ACFA were loaded on factors of three and four, respectively. In the end, the factor scores of the final factors generated were used to estimate the resilience LRI shown in equation (11).

$$LRI_n = (0.36570 * F1) + (0.20094 * F2) + (0.16054 * F3) + (0.12000 * F4) \tag{11}$$

Where, LRI_n = *livelihood resilience index of household n; F1, F2 ⋯ F4 = factor loadings.*

Except for CCV and S, all the latent variables showed a significant positive correlation with households' overall livelihood resilience index. However, ACFA revealed a lower correlation coefficient than the other latent variables. As applied by Dhraief et al. [50] and Daie and Woldtsadik [28], the study uses five ranges of LRI scores that are randomly proposed to group the levels of households'

Table 8
Communalities, factor loadings and correlations of the LRI latent variables.

Latent variables	*Communalities*		*Factor and their loads*				*Correlation to LRI*
	Initial	Extraction	1	2	3	4	
CCV	1.000	.742	.509	.020	−.326	.135	−.668**
S	1.000	.789	.541	−.275	.159	.011	−.756**
EIE	1.000	.749	.230	.270	.204	−.314	.713**
APT	1.000	.946	−.171	.936	−.196	.050	.552**
AP	1.000	.909	−.079	−.159	.912	.033	.434**
ACFA	1.000	.948	.025	−.024	.001	.925	.365**
Eigenvalues	Total		2.194	1.206	0.963	0.720	
	Variance (%)		36.570	20.094	16.054	12.000	
	Commutative (%)		36.570	56.663	72.718	84.718	

KMO test of sampling adequacy = 0.621
Bartlett's test of sphericity is significant at $p = 0.000$; Chi-square = 262.241
Extraction Method: Principal Component Analysis.
**correlation is significant at the 0.01 level (2-tailed)

CCV = climate change and Variability; S = sensitivity; EIE = enabling institution and environments; APT = Agricultural practice and technology, AP = asset possession; ACFA = adaptive capacity and food access.

livelihood resilience: highly vulnerable (LRI < −0.50), vulnerable (−0.50 ≤ LRI <0.10), moderately resilient (0.10 ≤ LRI <0.25), resilient (0.25 ≤ LRI <0.50) and highly resilient (LRI ≥0.50). Accordingly, as shown in Fig. 3, about 57% of the surveyed HHs were vulnerable, while 43.07% were resilient to different degrees (13.14% moderately, 16.79% resilient, and 13.14% highly resilient). Generally, the computed LRI ranges between −1.155 and 1.172, referring to the highly vulnerable and highly resilient HHs, respectively. Hence, over half of the households in North Wollo were not resilient at the time of the survey, and their livelihood activities were affected mainly by the droughts persistently occurring in the area.

3.3. Relative importance of latent dimensions to households' livelihood resilience

As shown in Table 10, the coefficient of determinism for the model is 0.998. This showed that all the independent variables combined together explained 99.8% of the total variations of the model. The result indicated that the selected independent variables are good predictors of the dependent variable. In the model, each latent dimensions does not have an equal contribution to the households' LRI. Although some of the variables have more influence in determining the LRI than others, each has an important role to play. Examining the standardized β coefficients in the output of multiple linear regression showed a significant ($p < 0.0001$) relative importance of each independent variable in influencing a dependent variable (LRI). Accordingly, irrespective of the negative signs, S (β = −0.372), CCV (β = −0.330), and EIE (β = 0.288) were the most important dimensions that contributed more in determining LRI, in respective order, than the others. This was followed by ACFA, APT, and AP. Hence, the absorptive capacity of HHs (CCV and S) showed the leading influence in determining LRI, while adaptive and transformative capacities had nearly similar effects. This finding agrees with the findings of Asmamaw et al. [26], who found that the absorptive capacity was the leading contributing factor to households' resilience to climate change-induced shocks.

The regression equation can be constructed using the unstandardized B coefficients, as per equation (4). So, the result indicated that rising sensitivity (S) by 1 unit decreases the LRI by a coefficient of 1.451, given that all other variables are constant (Table 10). This was also highly significant at $p < 0.0001$. The same analogy holds for changing the LRI in line with the B values of the other latent dimensions. Here, AP (B = 0.385) was recognized as the dimension having the lowest influence in determining households LRI, which possessed the minor relative importance (β = 0.19).

4. Discussion

In many parts of Ethiopia, differential livelihood vulnerabilities to climate-induced impacts were observed across different geographic locations [27], diverse livelihood zones, and wealth ranks of the farming households [30,52]. This potentially matters variation in the resilience capacity of smallholder farmers [51]. In the present study, the estimation of latent indicators of household livelihood resilience was mad possible using the three resilience capacities (absorptive, adaptive, and transformative). LRI as a continuous metric that shows where a household falls on the resilience-vulnerability continuum [28] revealed that over half (57%) of non-resilient respondents from their agro-based livelihood vulnerability situations and the impacts incurred.

Absorptive capacity of the households was explained by CCV and sensitivity (S) latent variables. All the variables used to determine the CCV score, except for one, showed a positive, significant ($p < 0.01$) correlation with the CCV itself (Table 2). Hence, all such variables have played an important role in estimating the CCV score. However, the variable "informed about CCV" showed a very week negative correlation with it. It is perhaps, though many of the farmers are informed about the CCV, they do not practically implement the necessary mitigation and adaption strategies that potentially raise farmers' resilience.

On the other hand, all the six sub-indicators which were applied to estimate sensitivity have a positive, significant ($p < 0.01$) correlation to the sensitivity itself (Table 3). Exceptionally, however, 'early warning information' and 'crop and livestock diseases' showed a stronger correlation ($r = 0.666$) than the others. One of the FGD discussants reported that *"when the DAs early warn us about the coming drought, everybody tried to make ready for it, especially, in terms of selling livestock before the price lowers, so that we can buy the food items and other demands. In addition, it can help us to undertake low, or 'no-regret' adaptation options proclaimed."* Similarly, Singh et al. [52] noted that during the 2015-16 drought, many households in Kombolcha (a place in Wollo) resorted to the undesired sale of livestock, particularly cattle and small ruminants. Hence, the more farmers are warned early and the less they are affected by crop and

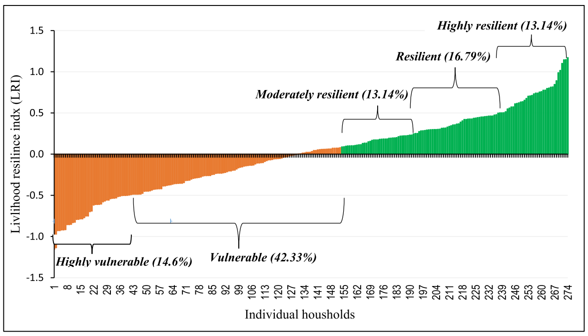

Fig. 3. Livelihood resilience index of households and their proportion by LRI levels.

livestock disease, the less they become sensitive to drought impacts and become more resilient. The FGD discussants also reported that households who participated in SWC could easily maintain their soil fertility and become more productive and wealthier. As a result, HHs having fertile farmlands are relatively less sensitive and likely more resilient to drought impacts than their counterparts. In agreement with this, Asmamaw et al. [26] and Tesso et al. [51] indicated that farmers in central highlands of Ethiopia who actively participate in SWC have fertile lands and are less sensitive and resilient to climate-induced shocks than their complements.

Adaptive capacity score of the system was estimated using adaptive capacity and food access (ACFA), and asset possession (AP) latent dimensions. Having saving accounts, radio or TV ownership, remittance, and farm size were the sub-indicators used to generate two factors (Table 5) to measure the AP score. Having a saving account and more money saved in it is a kind of security guarantee for HHs that enables them to fulfill farm inputs destabilized by drought impacts and thus resist any of the livelihood insecurity imposed. Similarly, remittance is the other means of income for the farming HHs to circumvent livelihood insecurity and improve their resilience. Radio and TV access help farmers to be informed about past, present and upcoming shocks, and making them ready with minimized risks. It also makes it easier for them to embrace new farming methods and technologies by allowing them to refine their shock adaption. Finally, the size of the land owned is also a relevant indicator of a household's ability to cultivate more and improve their livelihood or rent land and obtain income. In agreement with this, Weldegebriel and Amphune [29] emphasized that land is an essential productive resource in any rural community, and access to it defines the well-being of a specific livelihood. Likewise, Singh et al. [52] reported that household's ability to absorb drought stresses in northeast Ethiopia was connected to the size of land owned, the income obtained from different sources, savings, availability of water and livestock feed, among others.

It is also noted that all the variables (Table 5) are positively correlated with the latent variable AP and significant at $p < 0.01$. Among them, radio and TV ownership had the strongest association ($r = 0.76$) in comparison with the others. It was because the farming HHs who have radios, and very few of them TV, can easily access information and better cope and adapt to the drought-induced shocks than the others. In addition, farm size showed strong correlation ($r = 0.671$) with AP, indicating that the amount of landholding is crucial in asset building for the farming HHs [51] and so largely determine their resilience to climate-induced shocks.

Transformative capacity score of the system was observed using EIE and APT. Although they vary in strength, all the sub-indicators used to measure the EIE score revealed a positive significant ($p < 0.01$) association with EIE itself except for one (Table 6). However, in the present study, 'Distance to market' showed a very weak negative association ($r = -0.014$) with EIE showing that it has a feeble influence in determining their resilience to drought-induced shocks. Hence, access to institutions and basic infrastructure is crucial in improving farmers' resilience by making easy access to farm inputs, public services, information, and market exchange, and creating opportunities for livelihood diversification [37,51]. In contrast, all the seven sub-indicators that are used to measure the APT component have a positive correlation with the APT and are all significant at $p < 0.01$ (Table 7). Among them, application of herbicide ($r = 0.717$) and application of improved seeds ($r = 0.678$) showed a strong correlation with the latent variable. In contrast, training and support ($r = 0.39$) relatively exhibited the weakest association.

Generally, differences have been observed in the livelihood resilience capacity via the livelihood zonation and wealth ranks. The

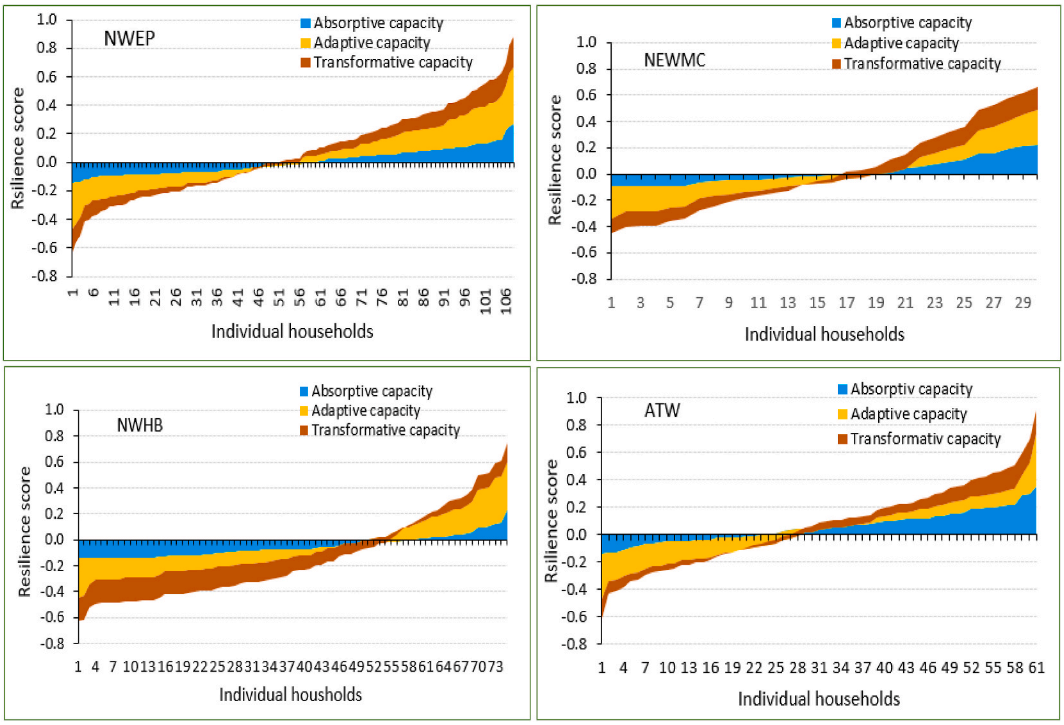

Fig. 4. Distribution of households by their resilience capacity scores in the four livelihood zones.

largest proportion of HHs in NWHB (72%) obtain a livelihood resilience capacity value below zero than the HHs in NEWMC, NWEP, and ATW, which obtained 53.3, 47.2, and 44.3%, respectively. This implies that the majority of less resilient HHs are living in NWHB and NEWMC livelihood zones than the rest.

However, when each of the resilience capacity scores was compared, the adaptive capacity of households showed the highest resilience score value in both positive and negative extremes (except for ATW), while their absorptive capacity was lowest in both extremes. This shows that the farming HHs of the different livelihood zones have nearly similar exposure to the CCV and sensitivity than the EIE and APT dimensions. On the other hand, the transformative capacity score of the households appears between the absorptive and adaptive capacity scores (Fig. 4). Hence, ACFA and AP showed more deviation in influencing farmers' livelihood resilience than the other latent variables used.

Regarding wealth ranks, about 86.4% of the better-off, 58.9% of the medium, and only 37.99% of the poor obtained a livelihood resilience score above zero. This implies that farming households are becoming more capable and more resilient to drought-induced livelihood impacts as their wealth status increases and vice versa.

In the study area, there exist a disparity in LRI value among the livelihood zones and wealth ranks (Table 9). From all the livelihood zones, the largest proportion of non-resilient HHs (77.33%) was found in NWHB, while ATW exhibits the largest percentage of resilient HHs (57.4%) with different resilience levels. The higher resilience of HHs in ATW was mainly because droughts in ATW were less persistent, enabling institutions were more accessible, agricultural inputs were more readily available, and the farming HHs were provided more training and support. In contrast, the NWHB livelihood zone showed the highest proportion of non-resilient households, mainly due to erratic and unreliable rainfall in the area, the smallest number of food self-sufficient HHs, poor access to social safety nets, relatively low asset possession, and lower perception and low preparedness to apply the remedial actions and technologies designed to cop and adapt to drought-induced livelihood impacts. The findings also revealed that the distribution of HHs throughout the resilience levels was not consistent across the livelihood zones.

As expected, the better-off were found to be more resilient than the medium and poor HHs. Therefore, only 9.1% better-off, 48% medium and 65.4% of the poor were found to be non-resilient HHs at the time of the survey. Among them, 6.7% of the households were poor but highly resilient, and the other 9.1% were rich but non-resilient. The poor but resilient HHs are those who were currently poor but characterized by relatively good scores in the CCV, S, EIE, and APT variables and the subsequent sub-indicators included in each. Hence, it is possible for such households to easily build their resilience through the targeted improvements of the identified defects.

This study has also compared the livelihood resilience of male-headed HHs (MHHs) and female-headed HHs (FHH). The findings indicated that over three-fourths (75%) of the FHHs were found to be non-resilient. In comparison, a soundly lower proportion (56.2%) of the MHHs were not resilient (Fig. 5). The MHHs in the area had better access to information, higher literacy levels, and decision-making power. As a result, HHs with higher educational status were better able to acquire and use the information and were better prepared to cope with and adapt to drought-induced livelihood impacts. In addition, the MHHs experience ownership, access to, and control over assets such as land, while the FHHs comparatively have low access to resources, social services, and credits, which substantively lower their resilience capacity. This study is in agreement with the findings of Mekuyie et al. [7], who reported that the MHHs were more resilient than the FHHs to climate-induced shocks. Similarly, the output obtained by Haque et al. [53] specified that the FHHs were less resilient than MHHs to climate-induced shocks and stresses.

The study was also trying to see the association of educational level, family size, farm size, and livestock holding (using tropical livestock unit (TLU) in 2019) of the households with their LRI score. The result indicated that farm size ($r = 0.329$), family size ($r = 0.294$) and livestock position ($r = 0.278$) showed a positive significant ($p < 0.01$) association with LRI. That is, such factors positively contribute to building the livelihood resilience of the farming households. On the other hand, the educational level of household heads showed a very weak ($r = 0.106$), non-significant correlation with LRI. Similarly, Asmamaw et al. [26] came to the same conclusion with most of these relationships. However, he has a contradicting finding on family size, where it was negatively correlated with HHs resilience. He reported that the probability of the household's resilience drops by 68% for each additional individual added to the household.

In the present study, many of the FGD discussants reported that *"family size is not a burden but a wealth."* Accordingly, households with more family members can efficiently perform their farming activities in a time of need, bringing additional income as daily workers for others. He/she can even temporarily go to the nearby towns as a daily laborer, and support their family. Hence, they are more resilient to drought impacts than those with fewer family members. Similarly, Dhraief et al. [50] reach the same conclusion as having a large family provides more stability in terms of food security, especially if the household has members who engage in off-farm activities.

Examining the standardized β coefficients in the output of multiple linear regression showed a significant ($p < 0.0001$) relative importance of each independent variable in influencing a dependent variable (LRI). Accordingly, irrespective of the negative signs, S ($\beta = -0.372$), CCV ($\beta = -0.330$), and EIE ($\beta = 0.288$) were the most important dimensions that contributed more in determining LRI, in respective order, than the others. This was followed by ACFA, APT, and AP. Hence, the absorptive capacity of HHs (CCV and S) showed the leading influence in determining LRI, while adaptive and transformative capacities had nearly similar lower effects. This finding is in agreement with the findings of Asmamaw et al. [26], who found that the absorptive capacity was the leading contributing factor to households' resilience to climate change-induced shocks. Generally, except CCV and S, all the resilience dimensions were found to influence the LRI positively. The low relative importance and influence of AP on the LRI of smallholder farmers were triggered by their small landholding (0.575 ha/household), poor access to information, low income, and low savings.

Table 9
Livelihood resilience index values by livelihood zones and wealth ranks in North Wollo, 2020.

Stratification		*Livelihood resilience index level (% of households)*				
		Highly vulnerable (LRI < −0.50)	Vulnerable (−0.50 ≤ LRI <0.10)	Moderately resilient (0.10 ≤ LRI <0.25)	Resilient (0.25 ≤ LRI <0.50)	Highly resilient (LRI ≥0.50)
Livelihood zone	*NWEP*	1.85	50.93	13.89	20.37	12.96
	NEWMC	10.00	40.00	26.67	10.00	13.33
	ATW	6.56	36.06	8.20	22.95	26.23
	NWHB	40.00	37.33	9.33	9.33	4.00
Wealth rank	*Better-off*	-	9.09	13.64	9.09	68.18
	Medium	5.48	42.47	9.59	27.40	15.07
	Poor	20.11	45.25	13.97	13.97	6.70

LRI = Livelihood resilience index; NWEP = North Wollo East plain; NEWMC = North east woina-dega mixed cereal; ATW = Abay Tekeze watershed; NWHB: North Wollo highland belg

Table 10
Relative importance of latent variables for households' livelihood resilience.

Latent variables	*Unstandardized coefficients*		*Standardized coefficients*	*t*	Sig.	*Collinearity diagnosis*	
	B	Standard error	Beta			Tolerance	VIF
Intercept	.002	.001	–	1.899	.059	–	–
CCV	−1.347	.012	−.330	110.823	.0000	0.732	1.366
S	−1.451	.013	−.372	115.635	.0000	0.629	1.590
ACFA	.817	.009	.249	93.324	.0000	0.913	1.096
AP	.385	.006	.190	68.475	.0000	0.844	1.185
EIE	1.437	.016	.288	87.501	.0000	0.601	1.663
APT	0.669	.009	.213	73.102	.0000	0.766	1.306

R^2 and adjusted $R^2 = 0.998$.
Dependent variable is LRI.
All latent variables are significant at $p < 0.0001$.
CCV = Climate change and variability; S = Sensitivity; ACFA = Adaptive capacity and food access; AP = Asset possession; EIE = Enabling institutions and environment;, APT = Agricultural practice and technology.

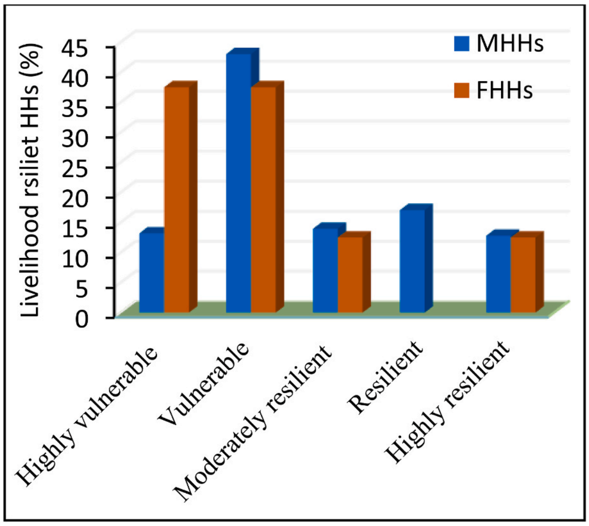

Fig. 5. Proportion of resilient households by gender of a household head.

5. Policy implications

Ethiopia is highly susceptible to drought, making it the most persistent disaster with prodigious influence on the country's economy, social well-being, and overall image over time [7]. The major drought periods in Ethiopia and the study area, in particular, were often followed by devastating famines [11], which made the problem more complicated and consequently sent the nation and its population highly vulnerable to the impacts [9]. Vulnerability, adaptation, and resilience are concepts that are gaining traction in various fields and policy implementations [54]. Though difficult and complicated to determine, resilience analysis helps to highlight the means of reducing the intended hardship [18], and obtain a complete understanding of the risk and vulnerability of the subjects [25]. Therefore, studying resilience can be a good way to assess how well a region is prepared for drought and ready to tackle the future.

Based on the results of this study, there is variation in resilience contexts across the livelihood zones and wealth ranks. Each of the six latent dimensions applied to measure the household's LRI was explained by variable score loadings of the variables used. Thus, the relative size of each variable's factor loading has substantial policy implications. The higher the load, the more critical it is, and the greater the policy focus should be.

To put it in plain words, the relative importance of each latent dimension of a household's livelihood resilience to drought impacts has clear policy implications for undertaking the necessary interventions and informing discussions for future planning in building livelihood resilience capacity. Therefore, future planning in building livelihood resilience capacity and drought risk interventions in the area should address the levels of resilience identified following the livelihood zonation and wealth ranks and the relative importance of each latent dimension indicated. It should also concentrate on developing locally relevant innovative solutions that support long-term resilience-building among the farming community.

6. Conclusions

The farmers' vulnerability to drought-induced risks depends on a household's exposure to risks and their resilience to such risks. Most drought risks are unpredictable, making it challenging to assess resilience. This study aimed to quantify and characterize the livelihood resilience of smallholder farmers in the face of recurring drought risks. PCA and regression models were applied to analyze the data gathered from surveys of 274 households. The LRI, framed on absorptive, adaptive, and transformative capacities, was used to quantify the households' livelihood resilience concerning livelihood zonation and wealth ranks.

The analysis shows that there was differential livelihood resilience capacity among the individual households, livelihood zones, wealth ranks, and gender of HHs. This was attributed to variations in each household's socio-economic situation, external exposure, and geographic location (agro-climatic and livelihood zone differences). In the area, only 43.1% of the surveyed households were resilient, while over half (57%) were non-resilient. From the livelihood zones, the highest proportion of non-resilient households (77.3%) was found in NWHB, whereas ATW exhibited the largest proportion of resilient ones (57.4%). Relatively lower persistence of droughts, better accessibility of institutions, more access to agricultural inputs, and the training and support given to the households attributed to the higher resilience in ATW. In contrast, NWHB showed the highest proportion of non-resilient HHs as a result of erratic and unreliable rainfall, the smallest number of food self-sufficient HHs, poor access to social safety nets, minimum asset possession, and their lower perception and preparedness to apply remedial actions and technologies designed. As expected, the better-off were more resilient than the medium and poor households. Remarkably, there were some better-offs but non-resilient, and some poor HHs but highly resilient.

The study noted that the absorptive capacity of HHs (CCV and S) were the leading in determining LRI, while adaptive and transformative capacities have nearly similar effects. Furthermore, all the six latent variables were not equally important for LRI. Consequently, S, EIE, and CCV were the most influential dimensions in respective order, which would play an important role in enhancing the resilience capacity households. These were followed by ACFA, APT, and AP, respectively, having a considerable long-term influence. In general, the applied resilience framework that takes into account household characteristics, wealth rankings, and livelihood zonation provides valuable guidance for understanding, initiating, and designing context-specific resilience programming. Finally, additional research in the study area and other localities is recommended to examine the resilience capacities of farming households, which are context-specific and may change if effective interventions are implemented.

Author contribution statement

Simachew Bantigegn Wassie: Performed the experiments; Analyzed and interpreted the data; Wrote the paper.
Daniel Ayalew Mengistu; Arega Bazezew Berlie: Conceived and designed the experiments; Wrote the paper.

Data availability statement

Data will be made available on request.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2023.e16422.

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