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Assessing the Alignment between Smallholder Farmers' Perceptions of Climate Change and Meteorological Data: Evidence from Agroforestry Systems in Gedeo Zone, Ethiopia

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Abstract

The aim of this study is to address how smallholder farmers perceived climate change and the need to analyze the link between local perceptions and climatic data, which is very crucial to design context interventions and policies toward supporting adaptation measures. This study collected data from 384 randomly selected respondents in 18 kebeles over three districts, using focus group discussions, climate data analysis (Mann-Kendall tau test and Sen's slope), descriptive statistics, and an order logit model. Most respondents reported that climate had changed notably with raised temperatures, declined rainfall, and a delayed rainy season as well as an increased intensity of drought and flood. Climatic patterns confirmed a significant increase in minimum and maximum temperatures during most seasons and years. While rainfall trends exhibited inter-seasonal variability, a significant increase was observed in long wet and autumn periods. Key findings reveal that the link between farmers' perceptions and climatic patterns revealed strong correlations with temperature changes but some inconsistencies regarding rainfall trends. The order logit model results revealed that the respondents' farm experience, educational level, livestock ownership, exposure to crop failure, total income, access to climate change information, and farmland fertility have significantly influenced their perceptions. Focusing interventions on these socio-demographic, institutional, and risk exposure variables will positively enhance farmers' perceptions of climate change, which, in turn, can contribute to enhanced ecological resilience to climate change.

Keywords: *Divergence analysis, climate change perception, Gedeo zone, meteorological trends, smallholder farmers*

1. INTRODUCTION

Agricultural stability across Sub-Saharan Africa (SSA) continues to be undermined by climate change, leading to a cascade of declining crop yields, spiking food prices, and increased exposure to environmental shocks, such as soil erosion and livestock mortality (Thakur and Bajagain, 2019). Nonetheless, agriculture remains the most effective engine of poverty alleviation and economic progress in the region, especially in Ethiopia where small-scale farmers contribute 95 percent of agricultural production and till 81 percent of temporal and permanent cropland (CSA, 2021). The sector accounts for 32.1 percent of the country's gross domestic product (NBE, 2023) and employed 77.3 percent of the country's labor force in 2021 (CSA, 2021). However, Ethiopia's agricultural sector is highly vulnerable to climate change, such as drought, flooding, desertification, water scarcity, and increased incidence of pests. Due to the country's economy relying on rain-fed agriculture and low adaptive capacity, it further increases its susceptibility to changes in climate-related shocks (EFCCC, 2021).

In response to these challenges, the Ethiopia government recently implemented the ten years' development plan inculcated the Climate Resilient Green Economy (CRGE) strategy and the National Adaptation Plan (NAP-ETH) to build climate resilient green economy (PDC, 2021). Despite these efforts, the country remains one of the most vulnerable countries in the world, ranked 37th most vulnerable for 2023 (NDGAI, 2023). Additionally, the country's vulnerability to changes in climatic conditions continues to be exaugurated by urban expansion, loss of farmland, deforestation, and political instability as well as economic constraints and weak institutional capacity (SIPRI, 2022). This is visible in densely populated and ecologically sensitive areas, such as the Gedeo Zone, where land pressure and environmental stress are already high.

The Gedeo agroforestry system is well recognized as diverse and sustainable due to its structure and design integrating trees and shrubs alongside other perennial crops, such as coffee and *enset* (Mengesha and Lulseged, 2021). The structured design of the system, beyond enhancing productivity also provides stability in the micro-climates by mediating temperature, reducing soil moisture loss and providing protection to the soil (Adane and Bewket, 2021). While this is a strength of the Gedeo agroforestry system, it is also its weakness as it requires the system to be in a delicate balance; so relatively little changes may have significant impacts. For example, increase in ambient temperature reduces shading capacity of trees causing coffee plants to be exposed to heat stress (Williams et al., 2017). As the soil becomes drier and the temperature rises the system is also vulnerable to pests and diseases that results in reduced yields (Adane and Bewket, 2021). To deal with these intertwined effects of climate change, it is critical to address issues of vulnerability (Thakur & Bajagain, 2019).

Although climate change is supported by scientific evidence, smallholder farmers' perceptions are equally important because it shapes how risks are understood and which adaptation choices are taken. Adaptation often begins with perceived change, yet inaccurate perceptions might lead to ineffective adaptation strategies choose, thereby failing to reduce vulnerability. Understanding how farmers perceive these changes, therefore, is essential, since perceptions strongly influence their adaptive behavior, as explained by the theory of planned behavior (Ajzen, 1991). Despite the importance of this system, there is still limited research that captures farmers' perceptions of climate change within such unique socio-economic and complex agroecological settings (Bogale, 2024; Demissie et al., 2025; Kerbo et al., 2022).

The Gedeo agroforestry system has been extensively investigated for its biophysical, ecological, spatial and temporal characteristics, and adaptation strategies (Fikadu & Azene, 2022; Gezahegn et al., 2025; Mebrate et al., 2022; Tadesse et al., 2020; Tesfaye & Nayak, 2022). Temperature and rainfall trend studies in Ethiopia have also produced a range of results, primarily because they vary by period, location and method (Belay et al., 2021; Dereje et al., 2020; Matiwos et al., 2022; Mekonen and Berlie, 2020). So far, no study has yet explored how farmers perceive climate change, how these perceptions compare with meteorological records, and which socio-ecological factors shape them in agroforestry systems in Southern Ethiopia. This study addresses this knowledge gap that calls for a systematic assessment integrating the farmers' perceptions of climate change with the observed climate trends in the agroforestry system.

To address these gaps, this study applies an ordered logit model to examine farmers' perceptions of climate change, identify factors explaining variation in these perceptions, and compare them with meteorological data. Unlike conventional models such as ordinary least squares, binary logit/probit, or multinomial logit/probit, the ordered logit model provides a more appropriate framework for analyzing ordered perception outcomes. The findings are expected to support the design of practical, context specific policies that reduce smallholder farmers' exposure to climate related risks.

2. Methodology

2.1 Biophysical Features of the Gedeo Zone

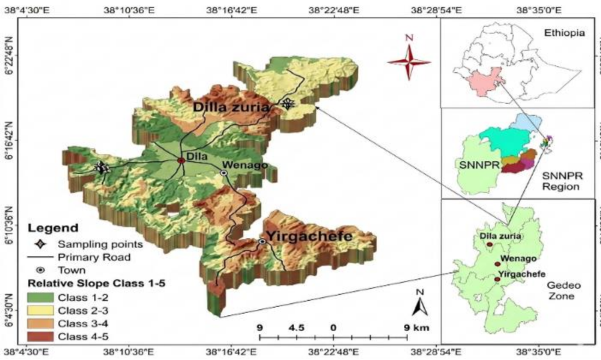
This research was conducted in Gedeo zone, particularly in *Dilla Zuria, Wenago*, and *Yirgachefe* districts owing to their closeness and common environmental setting. The districts are a part of the Rift Valley system which provided unique geological and ecological characteristics that could contribute to the present study outcomes.

As Figure 1 depicted that, the geographical boundaries of the selected districts, north of the equator between latitudes 6°4'30" N to 6°22'48" N and longitudes 38°4'30" E to 38°35'0" E. Based on these coordinates, the study area falls within the range of the Intertropical Convergence Zone

(ITCZ). Additionally, the area's distinctive landscapes, such as active fault lines, volcanic formations, and rich biodiversity, directly impact the environmental and social variables under investigation.

Figure 1

The map illustrates the study areas.



The total human population of the Gedeo zone is 1,251,620, with both sexes having equal representation, and 62% of the people live in rural areas (CSA, 2025). The elevation of the region ranges from 1758 to 2390 m.a.s.l (meters above sea level), which is characterized by a subtropical climate and is locally known as *Woinadega* based on traditional climate classification (MOA, 1998).

Based on estimation of recorded data (1990−2020), average total rainfall was around 1427 mm per year, with a minimum of 1062 mm, while a maximum of 2157 mm. Likewise, the average annual maximum temperature over the specified period varied between 22.06 and 28.03 °C, with annual maximum temperature of 26.69 °C. However, the average annual minimum temperature was recorded between 9.93 and 12.81 °C, with minimum temperature of approximately 11.56 °C per year. For detailed results of climatic data across three districts, please refer to Supplementary Tables S7, S8, S9, and S12, respectively.

According to Kippie (2002), the study area experiences both equatorial and monsoon trade winds, and its rainfall distribution is bimodal. The short-wet season (SWS), which represents rainy period from March-May, which falls in the spring season, peaking in April and May, whereas the long-wet season (LWS) falls between July and December (Kura, 2013; Tadesse et al., 2020).

Additionally, the same source stated that the winter season in this area is common in most parts of Ethiopia and is characterized by January and February as the dry months (*Bega*). However, autumn, locally called the *Mehir* season, falls from September to November (Kippie, 2002; Kura, 2013; Tadesse *et al.,* 2020).

2.2 Sampling Procedure and Sample Size

To select sample respondents, a three-stage sampling procedure was used. First, three study districts (*Dilla Zuria*, *Wenago*, and *Yirgachefe*) were randomly selected from the six districts of the study area (Gedeo zone) due to their similarity. Then, six kebeles were randomly selected from each of these three districts to ensure accuracy and to avoid bias. Thus, a total of eighteen rural kebeles from three districts were selected. Finally, 384 households were randomly selected from each kebele using a likelihood proportion probability to the population size method (PPPs). The sample size and selection method were determined based on Leslie's approach (Kish, 1965), as outlined in Equation (1), as follows:

$$n = \frac{z^2 pq}{e^2}$$

where ***n*** is the sample size to be determined, ***z*** is the value of the inverse of the standard cumulative distribution for the degree of trust (1.96), ***e*** is the degree of accuracy (level of precision) desired given a value of 5% (0.05), ***p*** is the proportion of respondents who perceived climate change in the population and q = 1 - ***p.***

To obtain a representative sample size for climate change perceptions in the large population with no information on variability, a proportion of ***p*** = 0.5 (maximum variability) was used as recommended by (Kish, 1965). Calculation was at 95% confidence level and 5 percent precision. The total sample size of the study was 384 respondents. This approach makes sure that the sample is statistically robust for population-level inferences.

2.3 Data Types, Sources, and Methodologies

This study has used both primary and secondary data sources to get a comprehensive picture. Primary data were collected through semi structured interviews with 384 household heads by trained enumerators familiar with culturally sensitive communication and local engagement. During the pilot study, the enumerators pretested the questionnaires with eight farm household heads in each district. This step helped refine the questionnaires and improve clarity before the main survey. Participants' feedback was systematically integrated to refine question clarity, reliability, and contextual relevance.

To improve clarity and cultural relevance, furthermore, survey questions were rephrased using locally resonant language, avoided jargon words, and mixed methods. To strengthen data reliability and validity, the study used personal interview schedules and focus group discussions. The study also used historical climate data, such as maximum and minimum temperature in degree Celsius and rainfall (RF) in millimeters obtained from Ethiopian Meteorology Institute (EMI) for the period 1990–2020. The period was selected because of availability of consistent climate records, minimal missing data and relevance for examining recent climate change across the selected study areas.

2.4 Inverse Distance Weighting (IDW) Interpolation Method

Before the climate data were analyzed, the study estimated missing values for meteorological datasets across the study locations. The missing values of rainfall and temperatures for this study were estimated using the Inversely Distance Weight (IDW) interpolation approach. The spatial distances between neighboring meteorological stations were calculated in Microsoft Excel 16 based on the geographical coordinates (longitude and latitude). The distance between each two stations was calculated using the Euclidean distance formula and weights were assigned inversely proportional to the distances. This was done to achieve uniformity of unit coordination and distance calculation.

The study acknowledges that more robust spatial interpolation functions might exist in specialized GIS or statistical software and recommends their use in future studies. Our estimation showed that the missing values in the climatic data were between 2.24 percent and 13.09 percent for the three districts studied. This method provided a more accurate and comprehensive dataset, being efficient and convenient for the subsequent analysis by averaging individual data from the three districts in question.

2.5 Data Analysis Techniques

2.5.1 Climate variability and trend analysis

Various definitions and thresholds for assessing wet days (threshold for wet days defined as the number of days with daily rainfall greater than or equal to 1 mm) and dry days (the criterion for dry days established as the count of days with daily rainfall below 1 mm), as has been used by other researchers (Omay et al., 2023; Sultan et al., 2019).

A coefficient of variation (CV) is employed to evaluate the interannual variation in rainfall and temperatures. The value of CV is calculated via Equation (2) as follows:

$$CV = \frac{\sigma}{\mu} X\ 100$$

where ***CV*** represents the coefficient of variation, σ represents the standard deviation, and μ represents the mean value of the climatic data over the reference period (1990–2020). While CV less than 20 percent stands for low variable data, CV from 20 to 30 20 percent refers to moderate variable data, and CV greater than 30 percent is defined as highly variable (Hare, 2003).

To characterize extreme weather events, the current study is employed the standardized precipitation index (SPI) at different time scales, as in (McKee et al., 1993), which uses a gamma distribution model fitted to an actual dataset for analyzing precipitation, providing a framework for understanding extreme weather events. Therefore, this study calculates the ***SPI*** via Equation (3) as follows:

$$SPI = \frac{X_i \mu}{\sigma}$$

where ***SPI*** denotes the standardized precipitation index; ***xi*** signifies the total rainfall for the chosen periods within the year; and ***μ*** and ***σ*** refer to the mean and the standard deviation of the long-term average rainfall, respectively. This study categorized the SPI values according to McKee et al. (1993).

Given the limitations of traditional regression methods, such as potential errors in coefficients estimation and reliance on normality assumptions for confidence intervals, as noted by Siegel and Castellan (1988). As a result, this study is employed Mann–Kendall's tau test, a non-parametric trend approach suitable for detecting monotonic trends over time without assuming any specific data distribution. This test helped to identify significant downward and upward trends in RF and temperatures over the specified period. In addition, the study was estimated Sen's slope estimator to quantify the intensity of these trends, which provides a strong estimate of the true slope in the presence of outliers or non-normal data distributions, giving precise rates of change per unit of time (Sen, 1968). A similar approach has been employed by previous studies (Bogale, 2024; Ortiz-Bobea et al., 2021; Wossen et al., 2017)

2.5.2 Analysis of farmers' perceptions of climate change

In this study, perception refers as the cognitive mechanism through which humans evaluate and organize sensory information to provide understanding of their surroundings, as defined by Ndamani and Watanabe (2015). Following the collection and analysis of the data, this study employed the score continuum Likert-type items as follows: strongly disagree = 1, disagreement = 2, indifferent/neutral = 3, agree = 4, and strongly agree = 5. From these seventeen indicators, the score continuum predicted a score range of 17–85. Ultimately, the study determined that each household had a normalized score, as calculated:

$$N_i = \frac{S_i}{S_{max}} \quad i = 1,2,3, \ldots ,384$$

where N_i is the normalized score for respondent (*i*), S_i refers to each respondent's score, and S_{max} is the maximum possible score over the sampled responses. Respondents were divided into three groups, which is estimated:

$$N_i^* = \begin{cases} H_p \; if \; N_i \geq \mu + \sigma \\ M_p \; if \; \mu - \sigma < \; N_i < \mu + \sigma \\ L_p \; if \; N_i \leq \mu - \sigma \end{cases}$$

where N_i^* refers to the household perception level of climatic change, μ is the average of the normalized scores, and σ is the standard deviation of the normalized scores. In addition, L_p, M_p, and H_p indicate low, moderate, and high perception levels.

2.5.3 Model Specification

The study treated respondents' perceptions of climate change as dependent variable, while the factors determining these perceptions were considered explanatory variables. Sampled respondents' perceptions of climate change were classified into three ordered groups: low, moderate, and high. Since these groups have a natural order, but difference between adjacent groups can not be assumed to be equal, the dependent variable has an ordinal nature. According to Greene (2012), ordered response models are appropriate for analyzing such variables. Conventional regression models are not suitable in this case because they assume interval level measurement, which does not apply to ordered categorical outcomes. The model's functional form specified as follows:

$$y^* = \sum_{k+1}^{k} \beta_k X_k + U_k$$

where y^* is taken as the latent variable, which might be the underlying tendency of an observed phenomenon; X_1, X_2, X_3, and X_n are vectors of explanatory variables; β_1, β_2, β_3, and β_n are confirmable parameter vectors of regression coefficients to be estimated; and U_1, U_2, U_3, and U_n are error terms with normal or logistic distributions with zero means. The results obtained as follows:

$$y = 1 \text{ if } y^* \le \mu_1, 2 \text{ if } \mu_1 < y^* \le \mu_2, 3 \text{ if } \mu_2 < y^* \le \mu_3,\ y = j \text{ if } \mu_{j-1} < y^* = 1,2,3,\dots,n$$

The general form for the probability that the observed ***y*** falls into category ***j***, which is estimated to be an ordinal logit model using specified as:

$$\mathrm{prob}(y = j) = 1 - L\left(\mu_{j-1} - \sum_{k+1}^{k} \beta_k X_k\right)$$

where ***L(.)*** represents the cumulative logistic distribution function.

Additionally, the marginal effects on the probability of each perception level were calculated as specified:

$$\frac{\vartheta\, prob(y = j)}{\vartheta X_k} = \left[f\left(\mu_{j-1} - \sum_{k+1}^{k} \beta_k X_k\right) - f\left(\mu_j - \sum_{k+1}^{k} \beta_k X_k\right)\right]\beta_k,$$

where ***f(·)*** denotes the probability density function.

In addition, this study was conducted a series of validation tests to ensure the robustness and appropriateness of the order logit model (OLM). Specifically, a link test was used to examine the connection between the independent variables and the cumulative probability of the response categories. More importantly, the study was applied five primary parallel regression assumption tests, including score, likelihood ratio, Wolfe–Gould, Brant, and Wald, which are essential for the model to work. This indicates that the associations between each pair of response categories, i.e., perception categories, are identical and so on (Williams, 2006). All analyses in this study were performed using Stata 17 software.

3. RESULTS AND DISCUSSION

3.1 Analysis of Meteorological Rainfall Data

3.1.1 Statistical analysis of seasonal and annual rainfall over time

The data reveals that the average total annual rainfall (ToTARF) was about 1427 mm, with values ranging from 1062 mm in the driest year (2004), to 2115 mm in the wettest year (2008). The monthly RF distribution indicates that May received the highest share of rainfall, accounting for 16 percent of the total, followed by April with 15 percent and October with 14 percent. In contrast, January, December, and February were the driest months.

Furthermore, the long-wet season (LWS) is the main contributor to ToTARF, with an average RF of 673.33 mm, representing 47 percent of the total. Rainfall during this season ranged from 383 to 1110 mm. The short wet season (SWS), which corresponds to spring, was the second major contributor, accounting for 39 percent of ToTARF, with rainfall ranging from 406 to 971 mm. In contrast, winter contributed very little to ToTARF because rainfall during this period was erratic and relatively low. This seasonal rainfall pattern is consistent with Ethiopia's bimodal climatic regime, which is mainly dominated by the LWS and SWS. Together, these two seasons provide 86 percent of the annual rainfall and are therefore critical for agricultural activities such as planting and harvesting. The strong dependence on the LWS also indicates that farmers may be vulnerable to climate change, especially if shifts in rainfall patterns disrupt the main rainy seasons. This finding is consistent with previous similar agroclimatic studies by Eshetu et al. (2016) and Kura (2013).

3.1.2 Analysis of temporal variability and trends in annual and seasonal rainfall

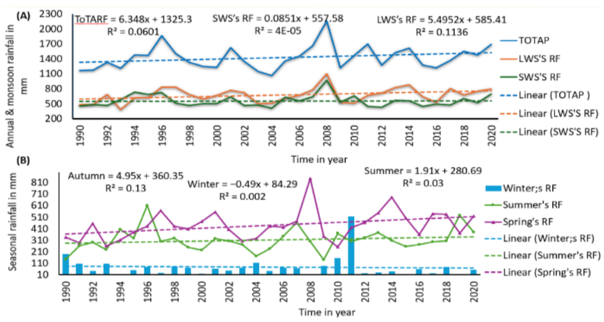
The yearly, seasonal, and monthly rainfall distribution from 1990 to 2020 in the study area is presented in this section. The data show that the average total annual rainfall (ToTARF) was about 1427 mm, with a standard deviation of 235 mm and a coefficient of variation of 16.5 percent. This indicates relatively stable interannual rainfall variability from one year to another. This finding is consistent with Alemayehu et al. (2020), who reported an increasing trend in annual rainfall in the *Alwero* watershed of western Ethiopia. Similarly, Lomiso (2020) and Ware et al. (2023) revealed an increasing trend in ToTARF along the Central Rift Valley escarpment of Ethiopia, within an altitudinal range of 1179 to 3127 m.a.s.l.

Regarding seasonal rainfall, the SWS, LWS, and autumn rainfall showed moderate variability, with coefficients of variation ranging from 21 to 28 percent. In contrast, winter rainfall showed a different pattern, with its coefficient of variation increasing to 119 percent, which was much higher than the 31 percent recorded for summer. These results are consistent with the findings of Belay et al. (2021) and Lomiso (2020). Although total annual rainfall appears relatively stable, seasonal irregularities remain a major challenge. These include unpredictable rainfall onset and cessation, as well as extreme rainfall events, which can disrupt agricultural planning and the cropping cycle. The gradual shortening of the long rainy season further increases the risk for rainfed agricultural production

The trend line analysis during the specified period revealed that increasing (6.348 mm) pattern of the annual rainfall (**Figure 2A**). In agreement with this finding, Alemayehu et al. (2020) revealed an increasing trend of ToTARF in Alwero watershed, western Ethiopia. Lomiso (2020) and Ware et al. (2023) also underscored an increasing trend of ToTARF in Sidama region, Ethiopia. Among the seasons, the LWS climbed fastest at 5.4952 mm (**Figure 2A**), followed by autumn at 4.95 mm (**Figure 2B**) and summer at 1.91 mm (Figure 2A). The SWS (spring) barely moved, gaining 0.085 mm, while winter rainfall fell by 0.49 mm (**Figure 2B**). These findings are consistent with the result of Alemayehu et al. (2020) and Ware et al. (2023).

Figure 2

Temporary trends in rainfall variability across the Gedeo zone (1990–2020)



The Mann–Kendall test further verified statistically significant positive rainfall trends during both the LWS and autumn at the 5 percent significance level, with Kendall's tau of 0.26 and p = 0.05. This result is supported by Sen's slope estimates, which indicate increases of 53.3 mm per decade and 49.2 mm per decade, respectively**.** Overall, rainfall exhibited an increasing trend on an annual basis and across most seasons, with the strongest increases observed during the LWS and autumn. These results are inconsistent with the results of the Ethiopian government which reported high rainfall variability since 1960s (EFCCC, 2021).

However, rainfall variability does not necessarily contradict an increasing trend as rainfall can increase over time and at the same time be more inconsistent. The results are also generally in line with the IPCC report which states that one-degree Celsius rise in air temperature may be associated with 1 to 3 percent increase in precipitation (IPCC, 2007). This association supports the current findings which show significant increases in both minimum and maximum temperatures on an annual basis and in most of the seasons and months in the study area from 1990 to 2020.

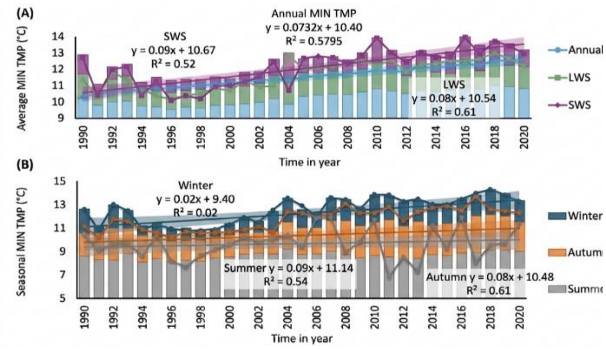
Another plausible explanation for the ellipsis in total rainfall is the modification in RF event characteristics, namely the alterations in frequency and intensity of rainfall events as elaborated **in Section 3.3**. This explanation is in line with the results reported by Pervin and Khan (2022), who found that the total rainfall increases each year was mainly ascribed to the increase in heavy rainfall events. Climate characterizations also reveal that precipitation patterns are altered in several regional settings, that have reportedly witnessed an upsurge in heavy rainfall events. The collective results suggest that the study area displayed discernible evidence of climate change between 1990–2020. These changes have important implications for agriculture activities due to rainfall and temperature directly influence crop cycles, soil stability, water availability, and food security. River changes in seasonal rainfall are of particular and paramount importance for coffee production, as flowering, fruiting and early crop development are sensitive to the timing and amounts of rainfall, as reported by Jayakumar et al. (2017).

3.2. Analysis of Trends in Annual and Seasonal Temperature Extremes

The regression analysis demonstrated a significant increasing trend of the annual and the seasonal minimum temperatures from 1990 to 2020. As illustrated in **Figure 3A** illustrated increasing of the annual minimum temperature was 0.07 °C (R^2 = 0.58), while the rate of the rate of the minimum temperature of the LWS and SWS with the spring development were 0.08 °C (R^2 = 0.61) and 0.09 °C (R^2 = 0.52), respectively. These findings indicated that the temperatures during the LWS and the SWS were much higher than those in the past.

Figure 3

Annual and seasonal minimum temperature pattern in Ethiopia's Gedeo Zone



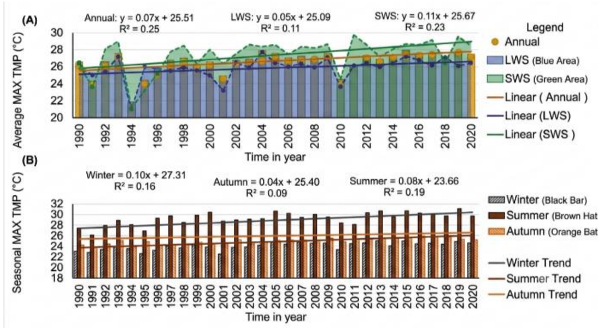
Note: Graph A illustrates the minimum temperatures recorded during the annual period as well as the wet seasons, namely the LWS and the SWS. Graph B depicts the minimum temperatures corresponding to the remaining seasons.
Data sources: Computed based on raw data from EMI, 2021.

As shown in **Figure 3B**, the minimum temperatures in autumn and summer were the two most significant warming signals with corresponding rates of 0.08 °C per year (R^2 = 0.61) and 0.09 °C per year (R^2 =0.54), respectively. Interestingly, the temperature trend in winter was weak, with an upward trend of only 0.02 °C per year, with a very low coefficient of determination (R^2 =0.02). It is evident from the results that minimum temperatures have risen rapidly during spring, summer, and LWS. The interpretation of this kinetic process may be partially explained by regional climate modifications.

The regression analysis in **Figure 4A** indicates a moderate upward trend with an increment of 0.07 °C per year (R^2 = 0.25) in the annual maximum temperature throughout the 1990–2020 period. The SWS (spring) had a steeper increasing trend of 0.11 °C per year (R^2 = 0.23) than the LWS which increased at a rate of 0.05 °C per year (R^2 = 0.11).

Figure 4

Annual and seasonal maximum temperature patterns in Ethiopia's Gedeo zone



Note: Graph A presents maximum temperatures during the annual period and the wet seasons, specifically the LWS and SWS. Graph B displays maximum temperatures for the remaining seasons.
Data source: Own sketch based on raw data from the EMI, 2021.

Mann-Kendall tau test pointed out the significant increasing trends of both annual mean maximum (τ = 0.41) and minimum (τ = 0.58) temperature in this period (1990–2020) as shown in Table S4 and Table S5, respectively. The Sen's slope test illustrated that the maximum and the minimum temperature increased by 0.4 and 0.8 °C per decade, respectively. Thus, the rate of increase in the nighttime temperatures is higher than the daytime warming in this study area. The result of seasonal warming trends indicates that the minimum temperature increased significantly during autumn, summer, spring, and the LWS period with the τ values (0.54–0.61; $p < 0.05$), while the increasing rate is 0.8–1.0 °C per decade. Maximum temperatures also showed seasonal warming with stronger increases observed during spring (τ = 0.35; 0.7 °C per decade) and winter (τ = 0.42; 0.8 °C per decade), whereas in summer (τ = 0.32), LWS (τ = 0.31), and autumn (τ = 0.17) only moderate rises of 0.5, 0.3 and 0.2 °C per decade were observed, respectively.

Comparisons indicate that the findings differ from previous studies in northeastern and southern Ethiopia (Ademe et al., 2020), where maximum temperature increased at a faster rate. On the other hand, corresponding observations of Cherinet and Mekonnen (2019) and Habte et al. (2022) also support our study, which has stronger trends for minimum temperatures. The results show that the annual and seasonal warming in the study area is mainly due to increase in minimum temperatures.

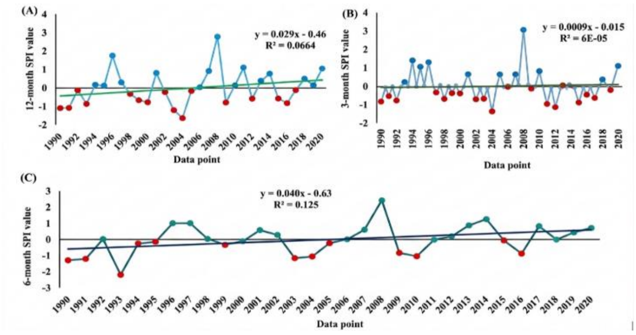
The most pronounced seasonal increases in minimum temperature occurred during spring and summer, while maximum temperatures rose more during winter and spring. Such changes, especially at critical periods of the agricultural cycle, could degrade crop productivity and ecosystem stability. The results indicate accelerating warming trends with important implications for agricultural productivity, water resources and adaptation to climate change in the study area.

3.3. Analysis of the Prevalence of Extreme Weather Events

As displayed in Figure 5, the study area exhibited significant variability in extreme weather conditions, marked by recurrent droughts and floods, as quantified through the Standardized Precipitation Index (SPI). Figure 5A illustrates that four hydrological drought years occurred during the study period: 1990, 1991, 2003, and 2004. The most severe drought was in 2004 (SPI = −1.70), while the others were moderate (SPI between −1.30 and −1.17).

Figure 5

Temporal variability of drought severity over different timescales in Gedeo zone



Note: Graph A illustrates the 12-month Standardized Precipitation Index (SPI), Graph B depicts the 3-month SPI, and Graph C presents the 6-month SPI, each representing different temporal scales of precipitation variability. Data sources: Own sketch based on raw data from the EMI, 2021.

On the other hand, extremely wet conditions were recorded in 2008 (SPI = 2.88), and very wet conditions in 1996 (SPI = 1.84). Moderate wetness was observed in 2007, 2011, and 2020 (SPI = 1.04 to 1.21). The remaining 22 years were within near-normal ranges. Overall, these trends show high variability in hydrological patterns under the specified historical period.

As shown in **Figure 5B**, three years experienced moderate agricultural drought. Five years—1994, 1995, 1996, 2008, and 2020, had wet conditions. Among these, 2008 was extremely wet (SPI = 3.15), 1994 was very wet (SPI = 1.51), and the others were moderately wet (SPI = 1.16 to 1.40). The remaining 23 years showed near-normal precipitation. These results suggest the likelihood of floods in extreme wet years.

Eight meteorological drought years are identified in **Figure 5C**, i.e., 1990–1993, 2003, 2004, 2010 and 2016. The year 1993 was an extreme drought year, and the other year was a moderate drought year. The wet years were 1996, 1998, 2008, 2013 and 2014, and 2008 is an extremely wet year (SPI = 2.54), and the other year is a moderate wet year (SPI = 1.01–1.34). These results illustrate the strong interannual fluctuations in precipitation and the vulnerability of the study area to both floods and droughts.

Furthermore, the decadal analysis of drought characteristics from 1991 to 2020 reveals clear temporal variations in drought frequency, magnitude, and intensity. The period 1991–2000 recorded six drought events with a total magnitude of 4.45 and an average intensity of 0.74, and the period 2001–2010 recorded five drought events only; however, the total magnitude increased by 0.01 (4.46) and intensity increased by 0.15 (0.89). The period 2011–2020 recorded four drought events, though there had been a significant reduction, from there and to the period 1991–2020, in total magnitude (2.50) and intensity (0.63). In total for the period 1991–2020, we recorded 15 drought events, with a total magnitude of 12.60 and an average intensity of 0.84.

These decadal shifts suggest a declining trend in both drought frequency and severity in recent years. A comparison of indices across three periods confirms this: frequency and intensity peaked in the second period (P2: 4.46 and 0.89, respectively), compared to the first (P1: 4.45 and 0.74), before declining sharply in the third period (P3: 2.51 and 0.63). This suggests that more frequent, above normal and extreme wet years will be more common after the onset of rain. Consistent with this finding, the findings of Belay et al. (2021) and Lomiso (2020) reported that the trend of 2000s summers were wetter than in the 1990s. Omay et al. (2023) found that the 2011–2020 period saw the highest average number of wet days in the IGAD region.

However, these results contrast with Alemayehu et al. (2020), who identified the 1990s as the wettest decade.

In connection with intensifying rainfall extremes, the Simple Daily Rainfall Intensity Index (SDII), and in the frequency of heavy (R10) and very heavy (R20) rainfall days exhibited notable increases in the study area. For instance, R20 exhibited high variability (CV = 60%). Overall, the region has experienced more above-average rainfall than below-average conditions in recent years, often marked by early onset and late cessation of rains. This increasing variability, marked by alternating droughts and extreme rainfall, signals growing climate-induced hydrological instability. The increasing frequency of extreme rainfall events, the increasing intensity of rainfall and the decreasing dry period imply the moderating effect of the warming climate on atmospheric water vapor, forcing a shift towards short-duration, high-intensity rain. These changes disrupt farming calendars, heighten flood risks, stress water infrastructure, and threaten both food security and ecological stability. These results indicate that the study area is more challenging by extreme rainfall events than overall precipitation. The results are consistent with earlier studies (Shawul and Chakma, 2020) that have associated even slight variations in timing, intensity, and duration of rainfall with considerable effects on the local economies, water use and ecosystems. In addition, several studies demonstrate that small differences in rainfall, time of rainfall, intensity and duration have a significant impact on local economies, water resource usage, and agricultural throughout (Moshe and Beza, 2024).

3.4. Analysis of Farmers' Perceptions of Climate Change with Meteorological Data

Most respondents perceived a general increase in temperature. These findings are consistent with historical data analysis which showed a general increase in the minimum and maximum temperatures in most seasons and years. These findings confirm the studies conducted by Cherinet and Mekonnen (2019) and Habte et al. (2022) that farmers' perception of temperature changes are consistent with the historical data. Respondents' perception of rainfall changes did not match the historical data although the latter shows increase in total rainfall, earlier onset, and later cessation of rains between 1990 and 2020. Most households perceived changes in rainfall amount, seasonality and timing differently. However, the responses of respondents including increased days of dry, drought, and frost events were consistent with the trends reported in the historical data. These findings are aligned with the observations of a considerable proportion of respondents. The variance between farmers' perception of rainfall changes and concurrent meteorological observations have been examined in several studies (Esayas et al., 2019; Lomiso, 2020; Mulenga et al., 2017).

Researchers in such studies have documented farmers perceived a fall in rain, yet meteorological observation of rainfall reveals an upward trend. These discrepancies could arise through several factors, such as biases in mean value estimation in meteorological observations, farmers' increased susceptibility to extreme events, and increased demand for water. Farmers' perceptions of rainfall trends heavily influenced by recent experiences rather than long-term climatic patterns. For instance, a multi-year drought may lead to a perceived decline in rainfall despite stable long-term averages. This aligns with the availability heuristic, where vivid or impactful recent experiences disproportionately influence risk judgments (Seo and Mendelsohn, 2006).

Farmers' increased water requirements could be linked with an increased scarcity of such a critical resource, fueled by a growing population and degradation in the study area. Additionally, perceived decrease in precipitation could be associated with rising climate change and drought frequency, as noted by Mlenga and Jordaan (2019) and Tfwala et al. (2017). Qualitative data shows farmers often cite recent unpredictable rains as evidence of climate change, regardless of statistical trends. This observation may help to explain the inconsistency in the farmers' perceptions of precipitation.

3.5. Smallholder Farmers' Perceptions of Climate Change

3.5.1. Categories of smallholder farmers' perceptions of climate change

According to Cortés et al. (2021), an acceptable range of 0.7–0.9 indicates high homogeneity and precision in ensuring a similar construct among items on each scale. Consistent with these findings, this study revealed that the reliability analysis using Cronbach's alpha for the items related to climate change in the Gedeo zone indicates a higher level of internal consistency. The overall Cronbach's alpha for the score was around 0.80, which considered very good. This suggests that the items measure a coherent underlying construct.

Before conducting further analysis, the distribution of the perception score variable was evaluated for normality using a Q-Q (quantile-quantile) plot. Most data points closely followed the reference line, indicating that the variable approximates a normal distribution. Although slight deviations were noted at the lower and upper ends, the overall pattern supports the assumption of normality. Based on this visual assessment, the perception score variable was considered appropriate for parametric statistical tests.

The following section examines smallholder farmers' perceptions of climate change and its reported effects on household livelihoods over time. The analysis highlights locally experienced climate-related shocks and their impact on small-scale farming systems.

To make the comparison and analysis easier, the respondents were grouped into three perception categories: low, moderate, and high. As shown in Table 1, more than half of the respondents had a moderate level of perception, accounting for 54 percent. This was followed by respondents with a high level of perception, who represented 25 percent of the sample. In comparison, about 21 percent of the respondents had a low level of perception. However, a very small number of respondents who did not fully understand the perception items were excluded from the analysis.

Table 1

Associations between perception scores and perception index categories

Perception level	No_	%	Cut-off point	F-test
Low	79	21	≤ 0.64	
Moderate	204	54	0.65-0.85	
High	94	25	≥ 0.86	
Total	377	100		76.89***

Table 1 presents the classification thresholds used to group respondents based on their climate change perception levels. Households with perception scores of 0.86 or higher were categorized as having high perception, those between 0.64 and 0.86 as moderate, and those at or below 0.64 as low perception. The mean perception score for the high group was 0.91 ± 0.04, for the moderate group 0.73 ± 0.06, and for the low group 0.61 ± 0.03. A one-way ANOVA test showed a statistically significant difference in average scores among the three perception groups ($F = 76.89$, $p < 0.01$).

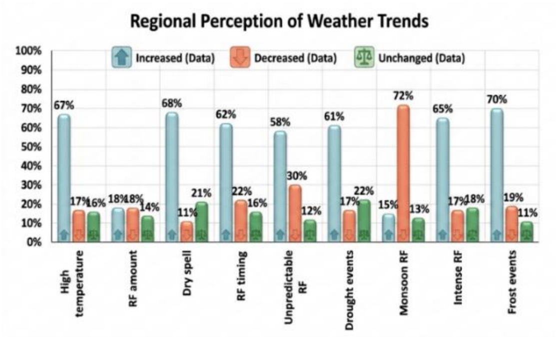
Additionally, Pearson correlation analysis found a strong positive relationship between group classification and average perception scores ($r = 0.84$, $p < 0.01$). These results are consistent with findings from previous studies (Abiyot, 2013; Daniel, 2019), which also observed variability in farmers' climate change perceptions. More recent work highlights that farmers with lower levels of awareness tend to focus on immediate livelihood concerns rather than long-term environmental issues (Legesse and Negash, 2021).

3.5.2. Perceived climatic shifts in rainfall and temperatures among farmers

The data revealed that survey respondents widely perceived rising temperatures, prolonged dry spells, and increased drought and frosty frequency. These trends align with regional studies in Ethiopia (Belay et al., 2021; Cherinet and Mekonnen, 2019; Habtamu et al., 2018; Habte et al., 2022; Lomiso, 2020; Ware et al., 2023) and global observations of shifting temperatures patterns (Mlenga and Jordaan, 2019; Tfwala et al., 2017). Furthermore, most of the respondents reported significant changes in precipitation patterns over 1990–2020, with perceived increases in uneven distribution and declines in seasonal/overall rainfall, as well as irregular rainfall timing and reduced totals (**Figure 6**).

Figure 6.

Pattern of smallholder farmers' perceptions of climate change in Gedeo zone



Focus group discussions (FGDs) corroborated these trends, emphasizing intensified rainfall episodes, delayed onset/cessation of rains, and resultant drier condition, challenges aligning with regional studies (Habtamu et al., 2018; Teshome et al., 2021; Lomiso, 2020) and global observations (Chepkoech et al., 2018). Overall, these findings indicate that temperatures and rainfall trends observed changes, marked by rising aridity, erratic rainfall, and delayed rainy seasons, underscore escalating climate vulnerabilities for Ethiopian smallholder farmers. These align with global trends of intensifying hydroclimatic extremes.

In this study, respondents widely recognized climate change impacts on the Gedeo home garden agroforestry, threatening livelihoods through environmental degradation and biodiversity loss. Key challenges included water scarcity, reduced crop yields, pest/disease proliferation, soil degradation, salinity, reduction in crop yields, and deforestation. FGD corroborated these findings, emphasizing linkages to marked-driven monocropping and ecosystem health declines (Daniel, 2019; Tadesse et al., 2020).

3.6. Factors Influencing Smallholder Farmers' Perceptions of Climate Change

Prior to employing the empirical model, different diagnostic tests were conducted, including checks for heterogeneity and multicollinearity using Breusch–Pagan test and Variance Inflation Factors (VIFs), respectively, as well as the link test, and the test of the parallel line's assumption The test of heterogeneity yielded a chi-squared statistic of 1.01 with a p-value of 0.3144, indicating no evidence of heteroskedasticity and supporting the assumption of homoscedasticity in the model. All VIF values for all independent variables ranged between one and less than three, indicating well below the commonly used threshold of 10 (Johnston et al., 2018).These results indicating no serious multicollinearity among the predictors, supporting the stability of the model's coefficient estimates.

Furthermore, the link test results revealed that the coefficient for the predicted value (_*hat*) was statistically significant at less than 5% confidence level. Associated with parallel lines assumption tests, all p-values from five diagnostic tests, including Wolfe Gould, Brant, Score, likelihood ratio, and Wald, exceed conventional significance thresholds (e.g., $p > 0.05$). These findings indicated no evidence against the parallel regression (proportional odds) assumption. Both results support the appropriateness of the ordered logit model for the data.

Findings in **Table 2** show that the ordered logit model provides a statistically significant improvement over the null model ($\chi^2 = 0.000$, $p < 0.001$). The McFadden pseudo-R^2 value of 0.1399 indicates a moderate model fit, suggesting the model improves prediction by 13.99% compared to an intercept-only model. Of the twenty-two explanatory variables, seven variables significantly influenced farmers' perceptions of climate change at different significant levels.

Table 2

Parameter estimates and marginal effects of the order logit model

Independent variables	Order logit model		Order logit marginal effects					
			Low perception		Moderate perception		High perception	
	Coef.	Std. errs.	dy/dx.	Std. errs.	dy/dx.	Std. errs.	dy/dx.	Std. errs.
Age	-0.013	0.011	0.002	0.002	3.4E-05	0.0002	-0.002	0.002
Family size	0.068	0.073	-0.010	0.011	-0.0001	0.0004	0.011	0.011
Farm experience	0.035***	0.012	-0.005	0.002	-0.0003	0.002	0.005	0.002
Education status	0.127***	0.035	-0.019	0.005	-0.0001	0.0001	0.020	0.005
Total cultivated land size	0.049	0.186	-0.01	0.029	-0.0002	0.001	0.008	0.029
Total annual income	4.8e-06*	2.7e-6	-7.3e-07	4.2e-07	-1.2-e08	5.8e-08	7.5e-07	4.2e-07
Livestock holding	0.061*	0.034	-0.009	0.005	-0.0002	0.001	0.009	0.005
Access to CC information	0.595**	0.286	-0.091	0.043	-0.002	0.007	0.093	0.045
Farmland fertility	0.482**	0.242	-0.074	0.036	-0.0012	0.006	0.075	0.038
Social capital	0.282	0.219	-0.043	0.033	-0.001	0.003	0.044	0.034
Contact with AEWs	-6.4e-03	0.091	0.001	0.014	1.6e-05	2.4e-04	-0.001	0.014
Received credit	0.186	0.233	-0.029	0.035	-4.7e-04	0.002	0.029	0.037
Use of irrigation	-0.155	0.286	0.024	0.044	3.9e-04	0.002	-0.024	0.044
Distance to market center	-1.7e-03	0.008	0.000	0.001	4.4e-06	3.1e-05	0.000	0.001
Cash crop orientation	0.049	0.137	-0.008	0.021	-1.3e-04	0.001	0.008	0.021
Exposure to crop failure	0.424*	0.238	-0.065	0.037	-0.001	0.005	0.066	0.036
Farmer to farmer extension service	0.205	0.312	-0.031	0.048	-0.001	0.003	0.032	0.048
Vulnerability status	-4.1e-03	0.220	0.001	0.034	1.0e-05	0.001	-0.001	0.034
Yirgachefe district	-0.585	0.401	0.095	0.065	-0.009	0.011	-0.086	0.057
Dilla zuria district	0.269	0.339	-0.038	0.047	-0.008	0.012	0.046	0.058
Cut1	3.017	0.925						
Cut2	5.728	0.959						

*Note: ***, **, and * refer to being statistically significant at the 1%, 5%, and 10% levels, respectively. CC = climate change, Coef. = Coefficient, Std. Err. = Standard error. Log likelihood = -345.10761, Wald chi2(22) = 105.66, chi2 =0.0000, and Pseudo R2 = 0.1399. Data Source: Own computation results based on survey data, 2021.*

In line with the initial hypothesis, the educational level of the household head had a significant positive influence on the likelihood of perceiving climate change ($p < 0.01$). This suggests that more educated household heads are more likely to recognize climate change compared to those with lower education levels. Specifically, a one-unit increases in education level raised the probability of moderate and higher perception categories by 0.01% and 2%, respectively, while reducing the likelihood of being in low perception category by 1.9%, ceteris paribus (**Table 2**). This finding can be attributed to the fact that higher education levels enhance households' access to information, understanding, and retention of climate-related issues. These results imply that formal education plays a crucial role in improving individuals' awareness of how climate change impacts local ecosystems and agricultural productivity, thereby affecting people's livelihoods. This conclusion is supported by complementary findings from previous studies (Emenyonu et al., 2020; Kerbo et al., 2022; Ndamani and Watanabe, 2015).

There was a statistically significant association between farming experience and perceived climate change ($p < 0.01$), as demonstrated by the statistics showing an increase in the likelihood of falling into moderate and higher perception categories by 0.03% and 0.5%, respectively, while decreasing the probability of falling into low perception levels by 0.5%, controlling for all other variables. This can be explained by households with extended exposure to agricultural practices accumulate substantial knowledge of local climatic patterns and anomalies. Over time, these farmers directly observe variations in rainfall, temperature, and the frequency of extreme events, enabling them to recognize long-term shifts indicative of climate change. Furthermore, repeated encounters with climate-induced risks, such as droughts and floods enhance their awareness of vulnerability and adaptive needs. This experiential learning fosters a heightened perception of climate change, even when controlling other socio-economic and demographic factors. These results are consistent with previous investigations, like the ones in Bangladesh (Haque et al., 2017), where a positive relationship between farming experience and climate change perception was also found.

The probability of perceiving climate change ($p < 0.1$) is significantly positively influenced by households with more livestock holdings. This suggests that households with larger livestock holdings are more likely to perceive climate change than those with fewer livestock holdings. Furthermore, each unit increases in livestock holdings led to a 0.02% and 0.9% increase in the probability of moderate and higher perception levels, respectively, but a 0.9% decrease in the probability of low perception, with all other factors held constant. This can be attributed to the fact that households with large livestock holdings often rely on livestock as an alternative source of income, making them more attuned to the impacts of weather and environmental changes on their animals. Their experience in animal husbandry and the time spent caring for livestock raise their sensitivity to shifts in climate patterns. These findings are supported by previous research conducted by (Abazinab et al., 2022; Opiyo et al., 2016; Snaibi, 2020).

As anticipated, household heads with access to climate change information were more likely to perceive climate change, with a statistically significant at p-value less than 5% confidence level. This finding suggests that households with greater access to such information better informed about climate dynamics than those with limited access. Assuming other factors remain constant, a one-unit increases in access to climate-related information raises the probability of moderate and higher levels of perception by 0.02% and 9.3%, respectively. In contrast, the probability of low perception decreases by 9.1%. This can be attributed to the fact that households with greater access to climate-related information tend to have a broader information base. This expanded knowledge enhances their understanding of the signs and impacts of climate change, making them more likely to perceive it as a significant issue. This finding is in line with the findings of empirical studies in Ethiopia (Asrat and Simane, 2018; Esayas et al., 2019). Similarly, previous studies also from other countries stated that climate-related information is very crucial for farmers that relied on rain-fed agriculture to enhance their agricultural productivity and income, thereby reducing climate-related risks (Lasco et al., 2016; Tesfaye and Nayak, 2022).

Household heads who perceived their farmland as infertile were significantly more likely to report awareness of climate change ($p < 0.05$). Controlling for other factors, a one-unit increase in the perception of infertility about their farmland raised the probability of falling into the moderate and high perception categories by 0.12% and 7.5%, respectively, while decreasing the likelihood of being in the low perception group by 7.4%. This suggests that perceptions of declining soil quality are closely linked to heightened perceptions of environmental stressors. Farmers who recognize the degradation of their farmland thereby become more attentive to broader environmental changes, including those climate-related shocks. The result aligns with findings from previous studies (Abdulai and Emmanuel, 2021; Abazinab et al., 2022). Their findings highlighted how such perceptions drive behavioral change. This finding is also supported by studies from other countries (Abdulai and Emmanuel, 2021).

According to Misachi (2024), previous exposures to environmental-related shocks has been shown to increase people’s perceptions of climate-related risks and understanding of climate dynamics. Recent research have also found that past crop failures led to farmers ready to adopt climate-smart practices, such as changing planting schedules and diversifying crops (Ogundeji and Okolie, 2022). In line with these findings, this study reveals that households that have experienced crop losses due to climate-related shocks are significantly more likely ($p < 0.1$) to perceive climate change as a serious issue. These households tend to fall into moderate or high perception groups more frequently than those without such experiences. Marginal effects estimates indicate that with each additional unit of crop failure exposure, the probability of a farmer falling into moderate and high perception categories increases by 0.011 and 6.60%, respectively. However, the likelihood of being in the low perception category decreases by 6.50%, holding other factors constant. This suggests that direct experience with crop failure considerably shapes farmers' perceptions of climate change. As farmers are increasingly affected by climate-related shocks, they are more likely to recognize the presence and seriousness of climate risks. These findings highlight the role of lived experience in influencing perception, potentially motivating greater interest in adaptation strategies.

Household income appears to play an important role in shaping perceptions of climate change. The analysis shows that households with higher total income is significantly ($p < 0.1$) associated with an increased likelihood of being falling into the moderate and high perception categories. Households with greater incomes may have better access to information, education, and extension services, which can enhance their awareness of climate-related risks. Additionally, higher income levels may enable households to observe and respond to environmental changes more actively, reinforcing their perception of climate variability and its impacts. Marginal effects indicate that as household income increases, the probability of being classified in the moderate and high perception groups rises by 1.21 x 10-6 and 7.46 x 10-5, respectively, while the likelihood of falling into the low perception category declines by 7.34 x 10-5. This suggests that economic capacity may influence how households interpret and prioritize climate risks, with better-off households more likely to recognize and acknowledge the challenges posed by climate-related shocks. The current study finding is consistent with existing literature that links socioeconomic status to environmental risk perception and adaptive capacity (Asrat and Simane, 2018; Marie et al., 2020).

4. CONCLUSIONS

The use of a mixed-methods approach provides a comprehensive framework for exploring the relationship between historical climate datasets and farmers' perceptions of climate change over time and identifying key factors influencing these perceptions. Although this area of research remains underexplored, it holds significant potential for bridging the gap between scientific data and on-the-ground experiences. Smallholder farmers in Ethiopia's Gedeo zone face serious challenges from climate change, mainly because they depend on rainfed agriculture and have limited means to adapt.

Analysis of Kendall's tau values to meteorological data indicate a notable rise in both maximum and minimum temperatures across all seasons, except during winter and on an annual basis. Rainfall patterns also showed seasonal variation, with significant increases during the long rainy season and autumn. These periods were marked by more frequent extreme weather events, including heavy rainfall and higher rainfall intensity, which have raised the risk of flooding. A substantial respondents reported shifts in climate patterns, including increased temperatures, decreased rainfall, timing of rainfall, and more frequent and severe weather events. Comparing climatic patterns with farmers' perceptions of climate change revealed strong correlations with temperature changes but some inconsistencies regarding rainfall trends. However, the mismatch between farmers' perception and recorded rainfall patterns underscores the need for targeted communication strategies. Simplifying meteorological data and using relatable examples can help farmers better understand rainfall variability and its implications for the ecosystem, particularly agriculture activities.

Additionally, the current study identifies seven factors that significantly influence farmers' perceptions, including educational, livestock holding, annual income, farming experience, climate change information, exposure to crop failure, and farmland fertility. Educational level emerged as a critical factor, promoting farmer-to-farmer knowledge exchange programs that encourage experienced farmers as community trainers. These programs should focus on climate-smart practices, soil conservation, and crop diversification. Integrate climate change education into adult literacy programs and local schools. Establish community-based climate information centres and strengthen linkages with local radio stations to disseminate seasonal forecasts and early warnings. Utilize mobile SMS alerts for real-time updates. Promote soil fertility restoration through organic composting, agroforestry, and integrated soil fertility management. Provide subsidized access to soil testing services and improved inputs. Encourage mixed farming systems that integrate crop and livestock production. Offer training on climate-resilient livestock breeds and fodder production. Diversify income sources through off-farm employment opportunities, value addition for coffee and *enset* (false banana), and small-scale agro-processing enterprises. Expand crop insurance schemes and promote drought-tolerant crop varieties. Support community seed banks to ensure access to resilient planting materials. By addressing these factors through tailored interventions, policymakers and development practitioners can improve farmers' perceptions of climate change, which, in turn, can contribute to more sustainable agricultural practices and enhanced resilience to climate variability.

Data availability

The data that supports the findings of this study can be obtained from the corresponding author upon reasonable request.

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Competing Interests

The authors declare that they have no competing interests related to this article.

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