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Original Research

Impacts of Climate Variability on Maize and Its Adaptation Practices In Bedele District, Southwestern Ethiopia

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Abstract

Climate change and variability are real global phenomena affecting agriculture, health, water resources, and the environment. This research examines the Effect of Climate Variability on Maize Yield and Household Adaptation Practices in Bedele District, *focusing on climate trends, impacts on maize yields, and factors influencing adaptation strategies. Using tools like R insat (7.16), XLSTAT (2018), and Stata (13), data were analyzed from the Ethiopian Meteorology Institute (EMI) and Woreda Agricultural Office. Results showed high variability in monthly,* belg, *and* bega *rainfall, while annual and* kremt *rainfall were less variable. The onset of rainfall (93.3%) occurred in April, and 63.3% of end dates fell in November, with less variability in the length of the growing period (LGP). Temperature analyses confirmed minimal variability in monthly, annual, and seasonal temperatures. Regression analyses indicated that the start of the season (SOS), end of the season (EOS), LGP, and* kremt *rainfall negatively impacted maize yields. Effective adaptation strategies identified included crop diversification, tree planting, irrigation, improved crop varieties, and soil water conservation. These were influenced by factors such as education, farm income, land size, credit access, and climate training. For example, education positively affected crop variety adoption and soil water conservation, while credit access negatively impacted tree planting. Policymakers and farmers should align practices with climate patterns, optimizing onset and end dates for better crop production. Promoting education, extension services, and access to climate training is essential to enhance adaptation strategies.*

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INTRODUCTION

Climate change, influenced by natural and human factors, poses a significant global threat. Since the industrial era, human activities, particularly rising greenhouse gas emissions, have accelerated global warming, with temperatures rising by 0.4°C since 1980 (IPCC, 2012; IPCC, 2014). Developing regions, especially Sub-Saharan Africa, are disproportionately affected due to limited adaptive capacities and reliance on climate-sensitive sectors like agriculture (Matewos, 2019).

In East Africa, rainfall variability has intensified, with long rains becoming drier and short rains wetter since the mid-1980s (Palmer *et al*., 2023). Ethiopia, where agriculture contributes 32.6% to GDP, 77% of exports, and employs 72.7% of the labor force, is particularly exposed to the impacts of climate change and variability (The Federal Democratic Republic of Ethiopia", 2024) Maize, a staple crop and key to food security, is cultivated by nine million Ethiopian smallholder farmers under diverse agro-ecological conditions (FAO, 2018).

Climate impacts on maize production are profound. Globally, maize yields declined by 12 Mt annually between 1981 and 2002 due to warming, and future temperature increases of 2°C and 4°C could reduce yields by 20–40% and 40–60%, respectively (Lobell et al., 2011; Tigchelaar et al., 2018). In Ethiopia, maize yields average 3.6 t/ha, below the global average of 5.6 t/ha, due to abiotic stresses like increasing temperatures, decreasing rainfall, and poor resource management (Tesfaye *et al*., 2015; Tolera *et al*., 2018).

Rainfall variability exacerbates challenges. Excess water during early growth stages hampers development, while reducing soil water during grain filling decreases yields (Hatfield and Prueger, 2011). Variability also limits agricultural input application, further reducing productivity (Kassie et al., 2014). While precipitation changes can sometimes mitigate temperature impacts, the relationship between rainfall and maize yield is complex, varying by region and conditions (Li *et al*., 2019).

Adaptation strategies are critical to counteracting climate impacts on agriculture. Climate-resilient crops, agronomic practices like irrigation scheduling, and integrated adaptation measures can enhance productivity and food security (Ahmed *et al*., 2023). Climate change poses serious threats to resource-poor farmers in Ethiopia, potentially leading to livelihood loss or forced displacement (Assan et al., 2018). Adaptation is therefore essential, but its success depends on locally tailored solutions that reflect specific environmental and socio-economic contexts. However, existing research often lacks focus on grassroots realities, offering generalized or policy-level insights with limited practical relevance. There is a clear gap in evidence-based, context-specific adaptation strategies that consider farmers' knowledge, constraints, and coping mechanisms in the study area. This study seeks to address the existing knowledge gap by identifying and evaluating effective, locally driven climate adaptation practices for vulnerable rural communities. Accordingly, the research was initiated to assess climate variability, its impact on maize yield, and the household adaptation strategies employed in Bedele District, southwestern Ethiopia.

MATERIALS AND METHODS

Description of the Study Area

The study took place in the Bedele area of the Buno Bedele Zone (Figure 1), located approximately 484 km southwest of Addis Ababa. This district comprises 41 kebeles and is geographically situated between latitudes 8°14'30"N and 8°37'53"N and longitudes 36°13'17"E and 36°35'05"E. It is bordered by Gechi district to the south, Dabo Hana district to the north, Chora district to the west, and Jimma Arjo district to the (BWAO 2023).

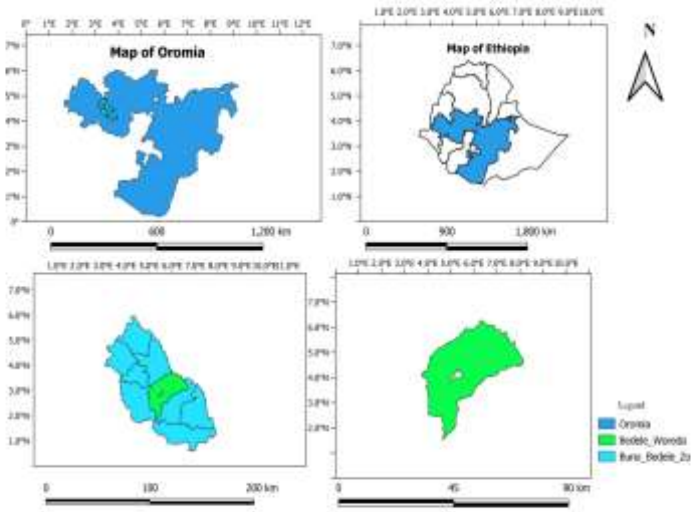

Figure 1: Location Map of the Study Area

Research Design

To assess climate variability, its impact on maize yield, and household adaptation practices, this study employed a cross-sectional survey design integrating both qualitative and quantitative research approaches. The quantitative aspect focused on analyzing maize yields, climate data, and household data. The qualitative component utilized information gathered through key informant interviews, focus group discussions (FGDs), household surveys, and questionnaires.

Types and Sources of Data

The study utilized a combination of primary and secondary data to incorporate both qualitative and quantitative elements. Primary data were collected through questionnaires, focus group discussions, and key informant interviews. Secondary data, daily rainfall, and temperature grid data for 31 years (1992–2022) were obtained from NASA's Earth Observing System Data and Information System (EOSDIS) and the local Natural Resources Office to assess climate variability. For the correlation and regression analysis between climate and maize yield, a 15-year dataset was used.

Sampling Techniques and Procedure

This study employed a multi-stage sampling technique to select kebeles (administrative units) and households systematically. Bedele District was purposively chosen for its maize production potential and its observed climate variability impacts on yield. Five kebeles Urgesa, Dabena Deru, Ilike Kerero, Kolo Siri, and Chilalo Bildima were purposively selected based on their agroecological diversity and maize production intensity. Systematic random sampling was used to select individual households. From the total 2833 households in these kebeles, 1979 were maize producers. Using Yamane's (1967) formula at a 92% confidence level, a degree of variability of 0.08, and a precision level of ±8%, the sample size was calculated as:

n = N/1+N $(e)^2$ ……………………………………………1

$$n = \frac{\mathbf{1979}}{\mathbf{1 + 1979\ (0.08)^2}} = \mathbf{145}$$

Where **n** is the sample size, **N** is the number of maize producers in the study area (1979), and **e** is the level of precision (8%).

Data Collection Tools

Household survey

A semi-structured questionnaire, based on the study's goals, was used to collect data from 145 households (April 12–September 20, 2023). It covered socioeconomic details, maize productivity impacts from climate variability, adaptation strategies, and influencing factors. To ease communication, it was translated into Afaan Oromo.

Key informant interview

Interviews were held with knowledgeable individual farmers, development agents, kebele officials, and district officers on climate impacts and local adaptation strategies.

Focus group discussion

FGDs involved 8–12 experienced male and female householders, selected with the help of village leaders, to discuss adaptation practices and the effects of climate variability on maize production.

Methods of Data Analysis

Analyses of rainfall and temperature variability

Thirty-one years (1992–2022) of daily climate data were analyzed to assess monthly, seasonal, and annual variability in rainfall and temperature. Descriptive statistics (mean, max, min, standard deviation) were computed using Excel 2016. Rainfall onset, cessation, Length of Growing Season (LGS), and the number of rainy days were determined using Excel and R Instat 7.16. Rain onset was defined based on Zewdu et al. (2005) and R. Stern et al. (2003) as the first occurrence of ≥20 mm of rainfall over 3 consecutive days after April 1st (the assumed planting date), with no dry spell longer than 9 days in the next 30 days. Cessation followed the criteria of Zewdu et al. (2005) and Stern et al. (2006), defined as the point after the first week of September when daily evapotranspiration exceeds rainfall, and soil water storage reaches zero.LGS was calculated as the number of days between onset and cessation. Rainy days were those receiving ≥0.85 mm, following Love et al. (2008). The Coefficient of Variation (CV) was used to assess variability:

CV% = $\frac{\alpha}{\mu}X100\%$ ……………………………………………………2

According to Hare (2003), climate is:

Less variable when CV < 20%

Moderately variable when CV = 20–30%

Highly variable when CV > 30%

Analysis of rainfall and temperature trends

Temperature and rainfall trends were analyzed to assess the direction, magnitude, and statistical significance of variability using the non-parametric **Mann-Kendall (MK) test** (Mann, 1945). This method is preferred for its robustness with non-normally distributed data and resilience to outliers. The MK test statistic (S) is computed as:

$$S=\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} \operatorname{sgn}(xj - xi) \quad \ldots\ldots 3$$

$$\operatorname{sgn}(xj-xi) = \int_{-1 \text{ if}(xj-xi)<0}^{+1 \text{ if}(xj-xi)>0} 0 \text{ if}(xj-xi)=0 \quad \ldots\ldots 4$$

Where xjx and xix_ are monthly, seasonal, or annual values and j>ij . A positive S indicates an increasing trend; a negative indicates decreasing.

The standardized test statistic Z is:

$$Z=\int_{\frac{s+1}{\delta} \text{ if } s<0}^{\frac{s-1}{\delta} \text{ if } s>0} 0, \text{if } s = 0 \quad \ldots\ldots 5$$

Positive values of the Z statistic indicate an increasing trend, while negative values indicate a decreasing trend. A trend is considered statistically significant when the absolute Z value exceeds the critical value Z1−αZ_{1-\alpha}Z1−α, with α set at 0.05 in this study (Mahmood, 2019), based on standard normal distribution tables.

Kendall's tau was used to assess the strength and direction of association between two variables (Mondal et al., 2012). Values range from –1 (perfect negative correlation) to +1 (perfect positive correlation), indicating how the ranks of paired observations move together.

The Sen's slope estimator was applied to quantify the magnitude of trends in seasonal and annual series (Wang *et al*., 2016). This method is robust against outliers and data errors (Simane et al., 2016). The slope β\betaβ is calculated as the median of all pairwise slopes between data points (Feng *et al*., 2016)

$$Q_i = \frac{xj-xk}{j-k}, \text{f or i=1, 2} \ldots\ldots \text{N} \quad \ldots\ldots 6$$

Where xj and x_k are data points at time j and (j>k), respectively. For all this analysis, XLSTAT 2018, which consists of a program of Mann-Kendall, was used.

Analysis of rainfall anomaly (extreme event)

The Standardized Rainfall Anomaly (SRA**)** was used to assess inter-annual variability relative to the long-term mean, helping to identify dry (negative values) and wet (positive values) years, as well as the frequency and severity of droughts (Woldeamlak & Conway, 2007; Ayalew et al., 2012). It is computed as:

$$\text{SRA (Z)} = (pt - pm) / (\sigma) \quad \ldots\ldots 7$$

Where Pt is annual (rainfall or temperature) in year t, Pm is long-term mean annual (rainfall or temperature) throughout observation, and σ is the standard deviation of rainfall Drought and wetness conditions were classified based on McKee et al. (1993) as follows:

Extremely wet: SRA ≥ 2, Very wet: 1.5 ≤ SRA < 2, Moderately wet: 1 ≤ SRA < 1.5, Near normal: –0.99 ≤ SRA ≤ 0.99, Moderately dry: –1.49 ≤ SRA < –1, Severely dry: –1.99 ≤ SRA < –1.5, Extremely dry: SRA ≤ –2. The analysis was performed using R Instant Version 7.16 and Excel 2016.

Correlation and Regression Analysis

To assess the impact of temperature and rainfall on maize production, both correlation and multiple regression analyses were performed using SPSS version 26. Maize yield (qt/ha) was the dependent variable, and the independent variables included Kiremt total rainfall, mean maximum and minimum temperatures, onset date, end date, and length of growing period (LGP). The Pearson correlation coefficient (r) was used to determine the linear relationship between maize yield and climate variables. The formula for Pearson's r is as:

$$r = \frac{n\sum xy-\sum x\sum y}{\sqrt{n\sum x^2-(\sum x)^2} x \sqrt{\sum y^2-(\sum y)^2}} \quad \ldots\ldots 8$$

Where; r = Pearson correlation coefficient between X (climate variables) and Y (maize yields); ∑X = Sum of the data in X distribution; ∑Y = Sum of the data in Y distribution; ∑XY = Sum of the product of X and Y; $\sum X^2$ = Sum of the squared X; $\sum Y^2$ = Sum of the squared Y; $(\sum X)^2$ = Squared of sum of X; $(\sum Y)^2$ = Squared of sum of Y; n = Number of pairs of the measurement. Where: coefficient (r) ranges from -1 to +1. A correlation coefficient (r) close to +1 indicates a strong positive relationship, -1 indicates a strong negative relationship and 0 indicates no relation**.** In the regression analysis, the effects of rainfall and temperature on maize yields were examined using the following model:

$$y = a + b1x1 + b2x2 + e \quad \ldots\ldots 9$$

y = Dependent variable (maize yield in quintals/ha), a = Y-intercept, b1, b2 = Regression coefficients for rainfall and temperature, x1, x2 = Independent variables (rainfall and temperature parameters), e = Error term or residuals. The **coefficient of multiple determination (R^2)** was used to assess how much of the variation in maize yield could be explained by the climatic parameters. R^2 is calculated as:

$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} \quad \ldots\ldots 10$$

Where SSE is the sum of squared error, SSR is the sum of squared regression, SST is the sum of squared total. In general, R2 measures how successful the fit is in explaining the variation of the data.

Econometric analysis

Econometric models like multinomial probit, multinomial logit, and multivariate probit (MVP) are key for analyzing categorical dependent variables. While the multinomial logit model is useful, it is limited by the independence of irrelevant alternatives (IIA) assumption, ignoring interrelationships between alternatives (Abrham et al., 2017; Lee Flang et al., 2015).

The MVP model addresses this by accounting for correlated error terms and interdependencies, making it suitable for studying simultaneous adaptation strategies like tree planting, soil conservation, and irrigation, which are often interconnected (Aemro et al., 2012; Piya, 2012). By relaxing the IIA assumption, MVP offers a more accurate view of decision-making. In this study, MVP was used to assess how factors such as sex, age, education, farm experience, income, and climate-related training affect adaptation to climate variability (Belay et al., 2017; Matewos, 2019; Gebrehaweria et al., 2016). Data analyzed with STATA version 16 highlighted that adaptation strategies are shaped by both observed and unobserved factors (Blederbos et al., 2004).

Y1∗=X1β1+ϵ1\[Y2∗=X2β2+ϵ2\[⁝ \[Yk∗=Xkβk+ϵk……………11

Y1∗, Y2∗,…, Yk∗ are the latent variables associated with each equation., X1,X2,…, Xk are the sets of explanatory variables for each equation., β 1β 2 ,…,β k are the coefficient vectors to be estimated and ϵ1,ϵ2,…,ϵk are the error terms, assumed to follow a multivariate normal distribution with mean vector 0 and covariance matrix ΣΣ.

RESULTS AND DISCUSSIONS

Climate Analysis

Rainfall analysis

Monthly rainfall analysis

Monthly-analyzed data from 1992 to 2022 indicated that the study area received the lowest mean precipitation in January (31.3 mm) and the highest in June (347 mm) (Table 1). The coefficient of variation (CV) analysis showed January rainfall was extremely variable (CV = 109.1%), while other months were highly variable except September, which had a relatively low CV of 29.2%. This suggests that overall rainfall in the area was moderately variable and less reliable. However, during the main growing season (June to September), when crop production is at its peak, rainfall is s more stable and thus more suitable for agriculture. Trend analysis further revealed that monthly rainfall increased over the 31 years, with an annual rise of 5.59 mm or 55.9 mm per decade (Figure 2). This finding contrasts with Atomsa & Zhou (2022), who reported a decreasing trend in monthly rainfall over the past 30 to 33 years. In contrast, key informants and focus group discussions (FGDs) indicated that rainfall has been decreasing in recent decades, except during the Kiremt season. They recalled that *the area was once covered with dense, evergreen forests, experiencing abundant rainfall, frequent cloud cover, and flowing streams. Even during the dry bega season, there was enough rainfall to support livestock with grass and water. However, participants linked the recent decline in rainfall to deforestation driven by population growth and agricultural expansion, as well as moral decline, which they believe has led to reduced crop yields, livestock losses, increased disease, and displacement.*

Table 1. Descriptive summary of monthly rainfall analysis

Variables	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Minimum	0.8	1.2	11.4	40.7	52.1	151.4	133.4	131.9	159.3	33.7	15.2	0.3
Maximum	170.6	103.6	205.3	333.3	686.1	543.4	498.4	587.8	417.3	394.5	171.1	140.9
Mean	31.3	36.7	84.0	174.0	306.0	347.0	305.2	291.8	271.6	189.4	81.8	35.9
SD	34.1	26.3	44.3	74.6	135.6	104.3	102.7	94.6	79.2	82.1	43.1	30.5
CV	109.1	71.7	52.7	42.9	44.3	30.0	33.6	32.4	29.2	43.4	52.7	84.9

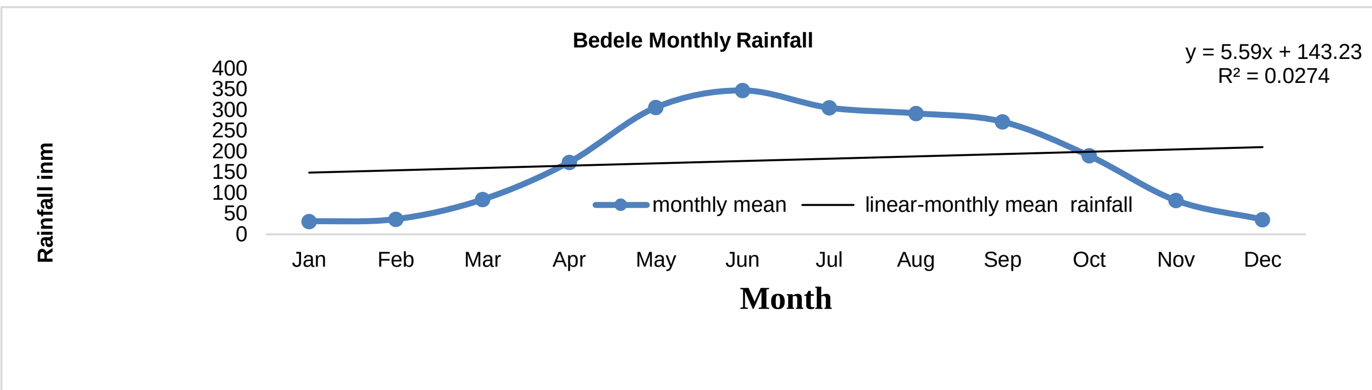

Figure 2: Bedele Monthly Rainfall (1992-2022)

Seasonal and Annual Rainfall Analysis

The study (Table 2) found the mean seasonal rainfall to be 600.7 mm (Belg), 1215.7 mm (Kremt), and 338.4 mm (Bega), with Kremt receiving the highest rainfall, consistent with Daba (2018). Coefficient of variation (CV) analysis showed higher rainfall variability in Belg (30.6%) and Bega (32.4%) compared to Kremt (25.8%), making Kremt more reliable. Belg and Bega rainfall showed increasing trends from 1992 to 2022, with Belg rising by 4.77 mm/year and Bega by 1.38 mm/year, aligning with Arragaw and Woldeamlak (2017), but contrasting with Orke *et al*. (2021), who noted a decline in Belg rainfall. Kremt rainfall, important for agriculture, increased by 8.7mm/year, supporting Arragaw and Woldeamlak's (2017) findings of a slight positive trend. The main rainy season (June to September) is crucial for agriculture, supporting both short and long-cycle crops. The area's annual rainfall ranged from 1073.5 mm to 2980.7 mm, with a mean of 2154.7 mm, increasing by 14.85 mm/year. The CV for annual rainfall (24.5%) was lower than Belg's, indicating moderate variability, contradicting Fenech *et al*. (2018) but aligning with Shawul and Chakma (2020).

Table 2: Descriptive summary of seasonal and Annual Rainfall of the Study Area

	Annual	Belg	kremt	Bega
Minimum	1073.5	192.8	681.2	122.2
Maximum	2980.7	1010.3	1725.3	613.3
Mean	2154.7	600.7	1215.7	338.4
S D	527.1	183.5	314.0	109.7
Cv	24.5	30.6	25.8	32.4

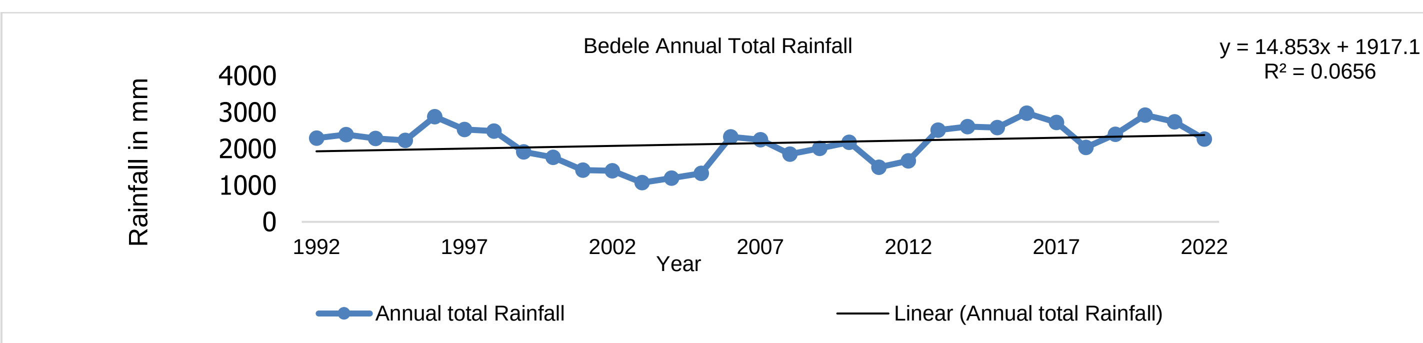

Figure 3: Bedele Annual Total Rainfall (1992-2022)

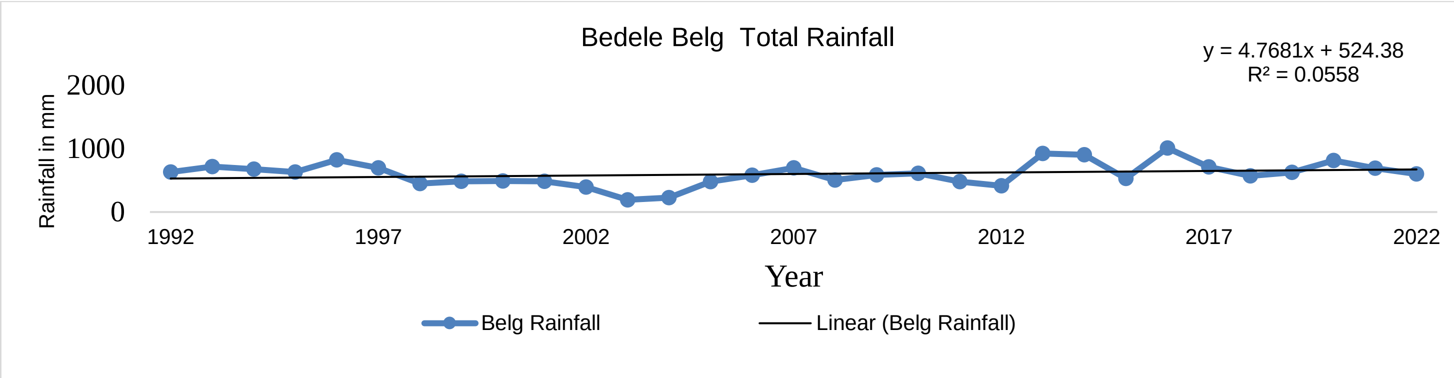

Figure 4: Bedele Belg Total Rainfall (1992-2022)

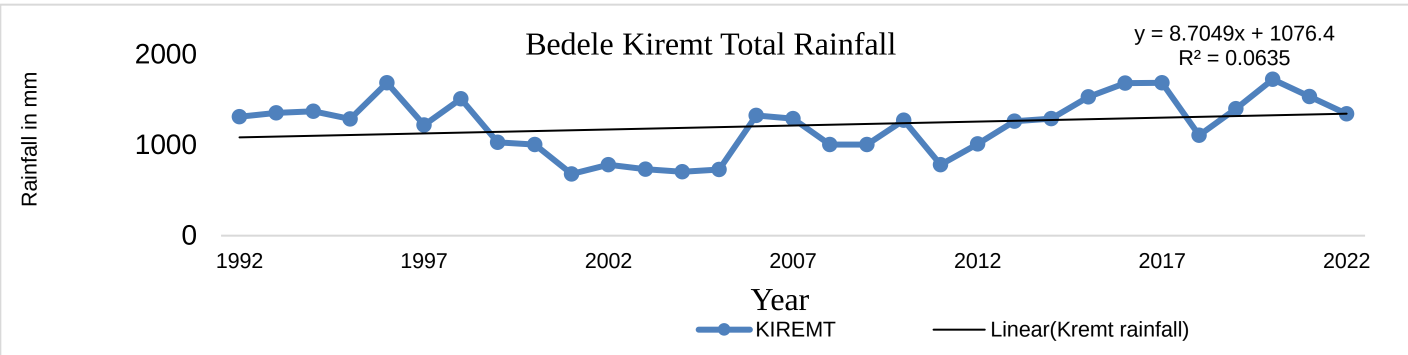

Figure 5: Bedele Kremt Total Rainfall (1992-2022)

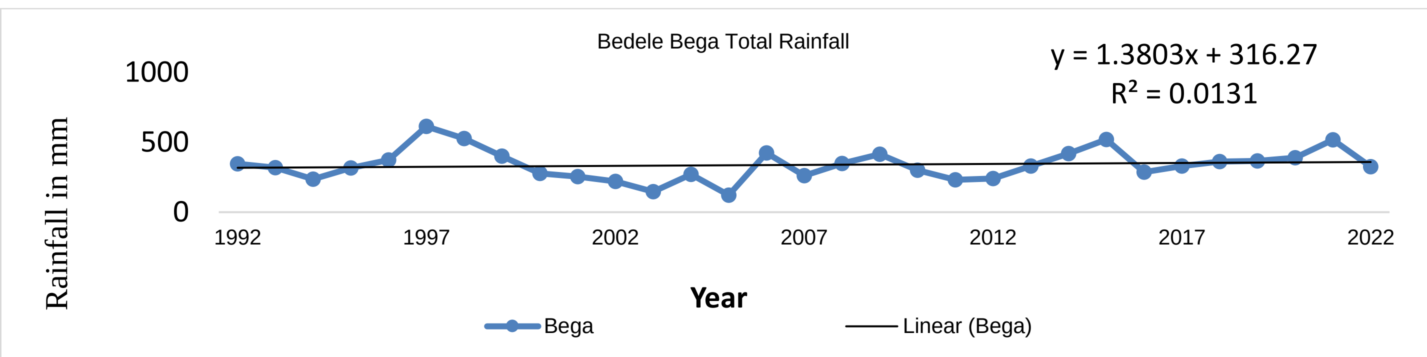

Figure 6: Bedele Bega Rainfall (1992-2022)

Analysis of Seasonal and Annual Start of rain, End of Rain, Length of Growing periods, and Rain days

Table 3 summarizes a 31-year analysis of seasonal rainfall in the Bedelle district. The earliest onset was April 1 (DOY 92) in 2002, 2017, and 2019; the latest was May 31 (DOY 152) in 2003, with a mean onset of April 26 (DOY 117). This contrasts with Mekonnen (2018), who reported a June onset for western Oromia. Onset variability was low (CV = 13.5%), and 93.3% of seasons began between April 1 and April 27. Seasonal rainfall ended as early as September 18 (DOY 262) in 2002 and as late as December 22 (DOY 357) in 2015, with a mean end date of November 8 (DOY 314). End date variability was also low (CV = 6%), differing from Mekonnen's mid-October cessation. Most seasons (63.3%) ended between November 1 and 24. The growing period ranged from 139 to 255 days, averaging 209.9 days (CV = 12%), indicating reliable length. Annual rainfall days ranged from 213 to 290, with a mean of 257 days (CV = 7.4%), showing consistency. Rain day variability was low for Kiremt (CV = 2.2%) and moderate for Belg (CV = 14.8%).

Table 3: Descriptive summary of Seasonal and Annual Start of rain, End of Rain, Length of Growing Periods, and Rain Days

Variables	Min	Max	Mean	Sd	Cv
SOS	92.0	152.0	104.0	14.0	13.5
EOS	262.0	357.0	314.	18.9	6.0
LGP	139.0	255.0	209.9	25.2	12.0
ANRD	213	290	257	19	7.4
KRD	113	122	120	3	2.2
BRD	34	81	55	12	20.9
BLRD	54	103	82	12	14.8

SOS=Start of Season EOS=End of Season, LGP-=Length of Growing Periods, ANRD=Annual Rain Day, KRD=Kremt Rain Day, BRD=Bega Rain Day, BLRD=Belg Rain Day

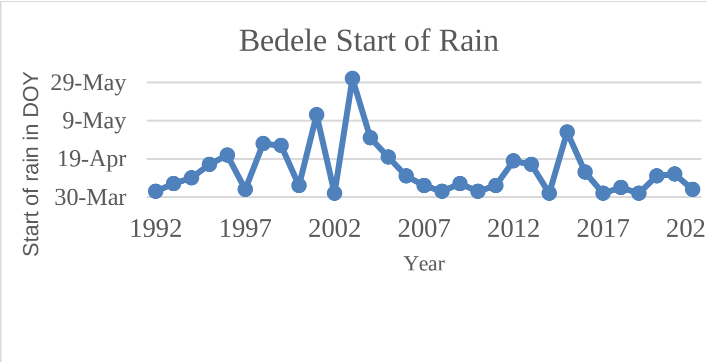

Figure 7: Bedele Start of Rainfall (1992-2022)

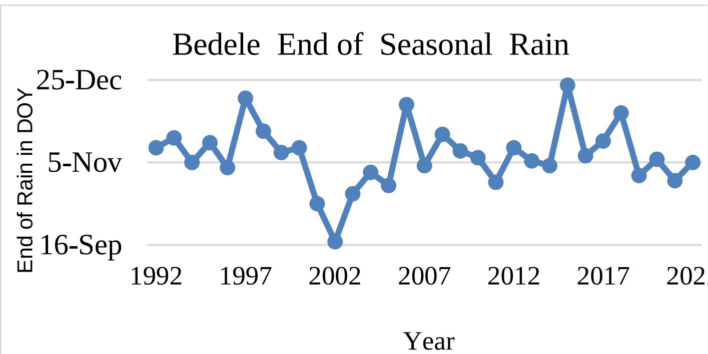

Figure 8: Bedele End of seasonal Rainfall (1992-2022)

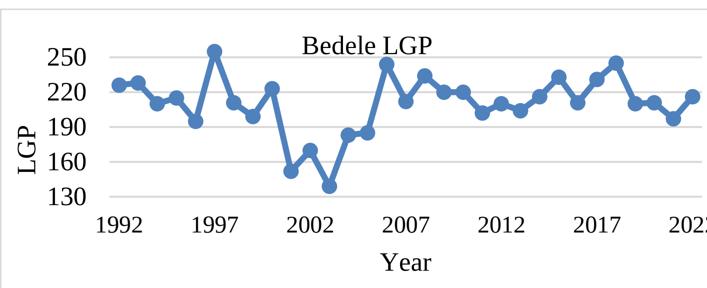

Figure 9: Bedele Length of Growing periods (1992-2022)

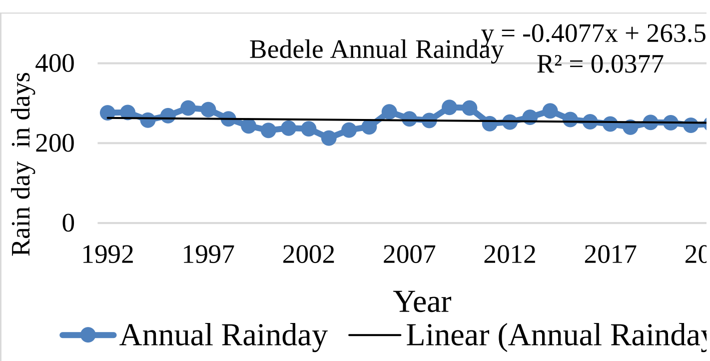

Figure 10: Bedele Annual Rain day (1992-2022)

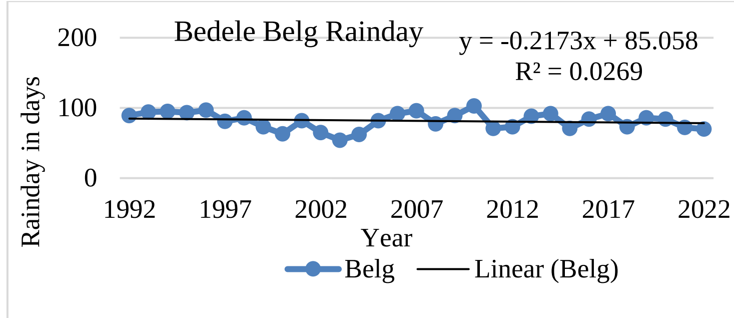

Figure 11: Bedele Belg Rain day (1992-2022)

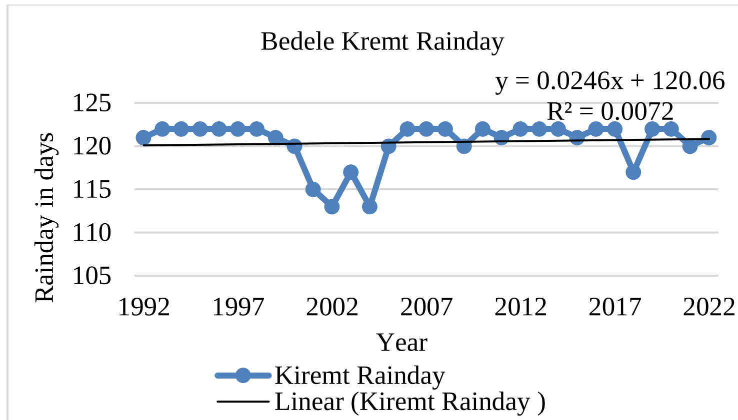

Figure 12: Bedele Kremt Rain day (1992-2022)

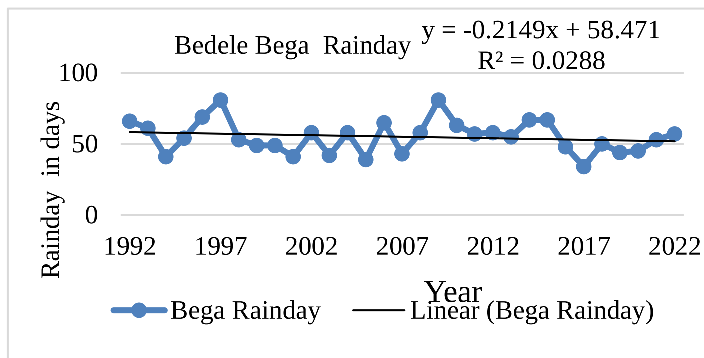

Figure 13: Bedele Bega Rain day (1992-2022)

Annual standard rainfall anomaly

According to Agnew and Chappel (1999), the standardized rainfall anomaly in the study area ranged from extremely wet to severe drought. In 2016, it was classified as very wet (Z = +1.6), while in 2004 experienced severe drought (Z = -1.8) (Figure 14).

Figure 14 shows extremely wet years in 2016 and 2020, and very wet conditions in 1996, 2017, and 2021. Moderately wet conditions were recorded in 19 years, including 1992–1995, 1997–2000, 2006–2010, 2013–2015, 2018, 2019, and 2022, representing 66.7% of the study period. Moderate droughts occurred in 2001, 2002, and 2005, while 2003 and 2004 experienced severe drought. Overall, the annual rainfall anomaly increased by 0.028 mm per year, aligning with Gemachu and Melkamu (2022), who reported a 0.008 mm increase from 1997 to 2017 in Bedelle.

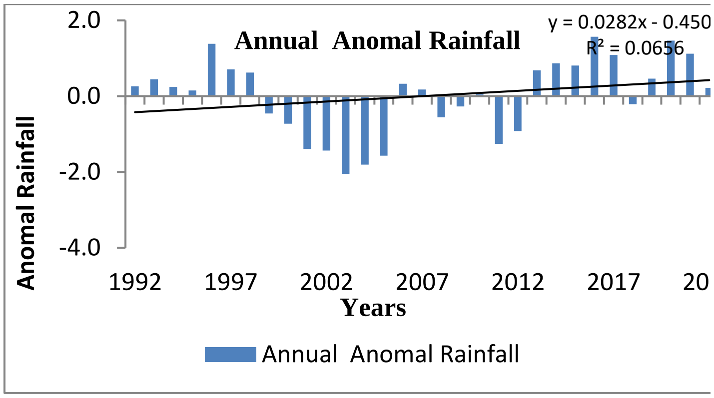

Figure 14: Bedele Annual Standard Rainfall Anomaly (SRA) (1992-2022)

Analysis of monthly minimum temperature

The analysis of 31 years of minimum temperature data (Table 4) reveals that monthly minimum temperatures in the study area range from a low of 8°C in December to a high of 14.7°C in May. The variability in these monthly minimum temperatures is low, with coefficients of variation ranging from 1.8% in August to 10.5% in December, indicating that minimum temperatures are generally reliable. However, there has been a decrease of 0.14°C per year, equating to a decline of 1.4°C per decade (Figure 15)

Table 4: Descriptive Summary of Monthly Minimum Temperature

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Minimum	8.3	10.5	12.3	12.9	13.0	12.4	11.8	12.2	11.9	10.5	9.1	8.0
Maximum	12.7	13.7	14.3	14.6	14.7	13.7	13.2	13.1	13.2	12.9	12.6	12.0
Mean	11.0	12.3	13.3	13.7	13.8	13.2	12.5	12.6	12.7	12.0	10.6	10.3
Sd	0.9	0.7	0.5	0.4	0.4	0.3	0.3	0.2	0.4	0.6	0.8	1.1
Cv	8.3	5.6	3.8	2.9	2.7	2.4	2.6	1.8	2.9	5.0	7.8	10.5

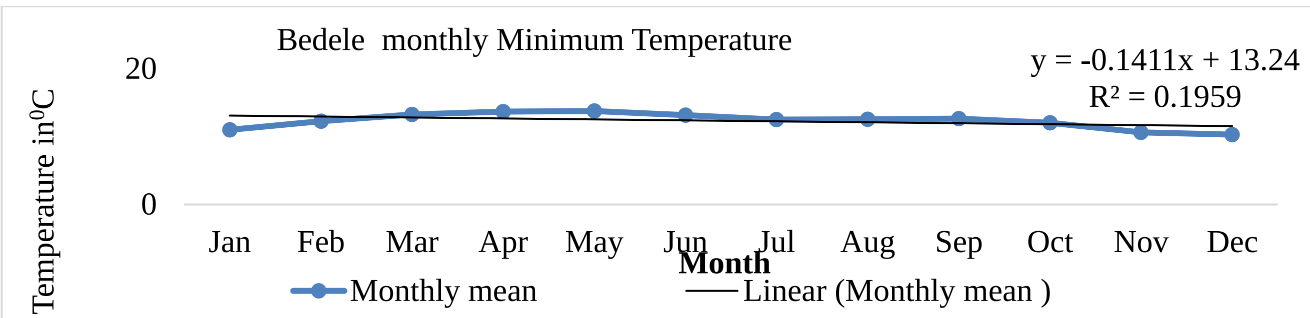

Figure 15: Bedele Monthly Minimum Temperature (1992-2022)

Analysis of seasonal and annual Minimum temperature

The annual minimum temperature in the study area ranged from 11.8 °C to 12.8 °C, with a mean of 12.3 °C and low variability (SD = 0.3 °C, CV = 2.1%). Seasonally, minimum temperatures averaged 13.2 °C in *Belg* (12.6–14.1 °C), 12.7 °C in *Kiremt* (12.2–13.3 °C), and 11 °C in *Bega* (9.7–12.2 °C), all showing low variability. From 1992 to 2022, minimum temperatures showed an increasing trend, rising annually by 0.0093 °C (or 0.093 °C per decade). Seasonal increases per year were 0.0185 °C (*Kiremt*), 0.0052 °C (*Belg*), and 0.0043 °C (*Bega*). These trends are consistent with Tolosa *et al*. (2023), who reported significant warming of 0.12 to 0.54 °C per decade in annual temperature extremes.

Table 5: Descriptive summary of Seasonal and Annual Minimum Temperature

	Annual	Belg	Kremt	Bega
Min	11.8	12.6	12.2	9.7
Max	12.8	14.1	13.3	12.2
Mean	12.3	13.2	12.7	11.0
S D	0.3	0.4	0.3	0.5
Cv	2.1	2.9	2.1	4.9

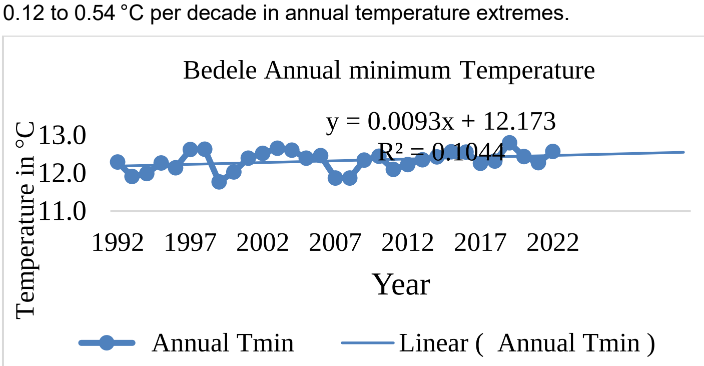

Figure 16: Bedele Annual Minimum Temperature (1992-2022)

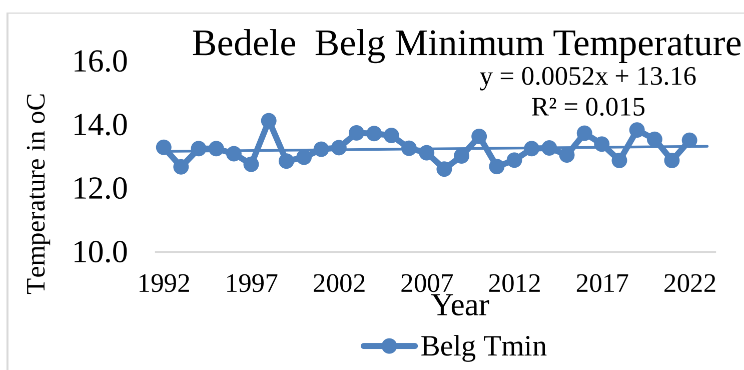

Figure 17: Bedele Belg Minimum Temperature (1992-2022)

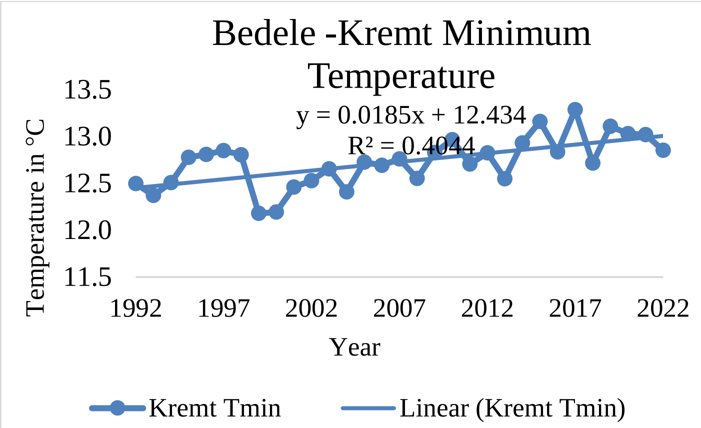

Figure 18: Bedele Kremt Minimum Temperature

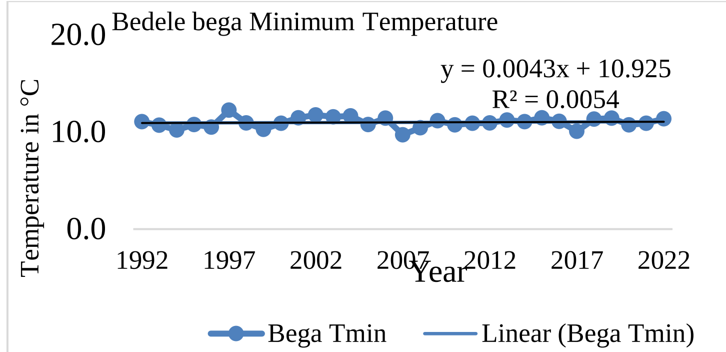

Figure 19: Bedele Bega Minimum Temperature

Analysis of monthly maximum temperature in the study area

Table 6 summarizes the maximum temperature data, showing that the lowest recorded maximum temperature was 18.8°C in July, while the highest reached 29°C in March. The monthly mean maximum temperatures ranged from 19.8°C in July to 25.9°C in March. Similar to the minimum temperatures, the variability in monthly maximum temperatures is relatively low, with coefficients of variation (CV) ranging from 1.7% in August and September to 6.8% in May (Table 14). Despite this low variability, there is a noticeable decreasing trend in monthly maximum temperatures, with an average decline of 0.3996°C (Figure 20).

Table 6: Descriptive Summary of Monthly Maximum Temperature

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Minimum	21.4	22.6	23.7	21.7	20.7	19.6	18.8	19.4	19.7	20.0	20.2	20.8
Maximum	26.8	28.9	29.0	27.7	28.6	21.5	20.5	20.8	21.1	22.0	23.3	24.7
Mean	23.2	25.1	25.9	24.2	22.3	20.4	19.8	20.1	20.4	20.8	21.1	21.7
Sd	1.4	1.7	1.3	1.3	1.5	0.5	0.4	0.3	0.4	0.4	0.5	0.9
Cv	5.9	6.6	4.8	5.5	6.8	2.5	2.2	1.7	1.7	2.0	2.6	4.1

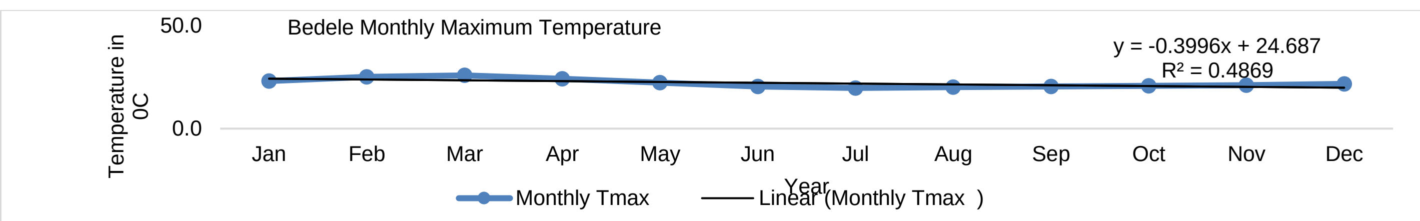

Figure 20: Bedelle Monthly Maximum Temperature

Analysis of seasonal and annual maximum Temperature

The study area's annual maximum temperature ranges from 21.1 °C to 24.0 °C, with a mean of 22.1 °C, SD of 0.6 °C, and CV of 2.8%, indicating moderate variability (Table 7). In the *Belg* season, temperatures range from 22.6 °C to 27.7 °C (mean: 24.4 °C), with low fluctuation (SD = 1.1 °C, CV = 4.5%), suggesting a pleasant, stable climate. During *Kiremt*, maximum temperatures vary from 19.6 °C to 20.7 °C (mean: 20.2 °C), with low variability (SD = 0.3 °C, CV = 1.6%). For *Bega*, the maximum temperature ranges between 20.8 °C and 23.8 °C (mean: 21.7 °C), with moderate fluctuation (SD = 0.7 °C, CV = 3.0%). These seasonal insights are important for climate monitoring and planning.

Table 7: Descriptive summary of seasonal and annual Maximum Temperature

Variable	Annual	Belg	Kremt	Bega
Min	21.1	22.6	19.6	20.8
Max	24.0	27.7	20.7	23.8
Mean	22.1	24.4	20.2	21.7
S D	0.6	1.1	0.3	0.7
CV	2.8	4.5	1.6	3.0

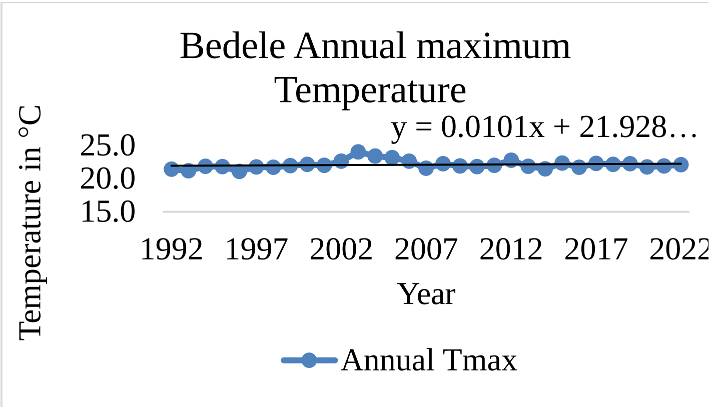

Figure 21: Bedele Annual Maximum Temperature (1992-2022)

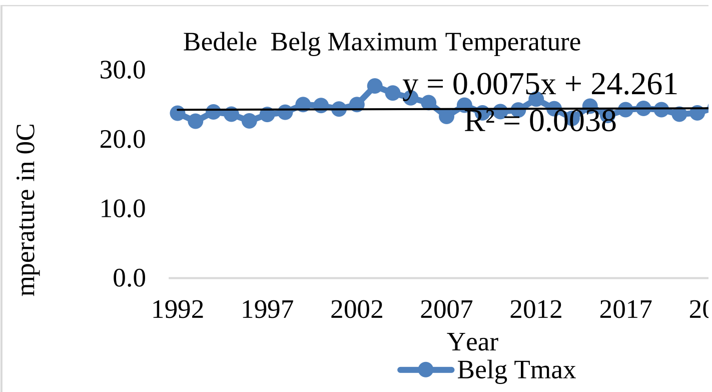

Figure 22: Bedele Belg Maximum Temperature

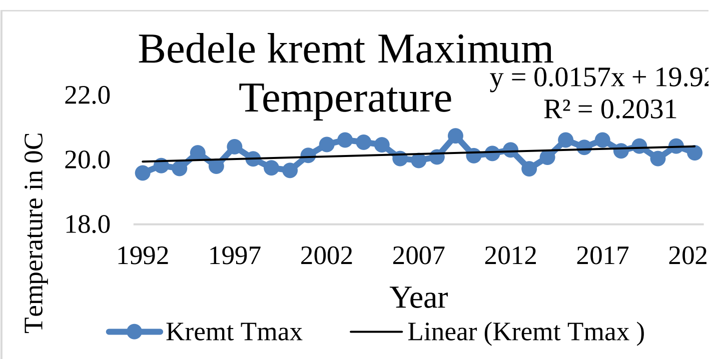

Figure 23: Bedele Kremt Maximum Temperature (1992-2022)

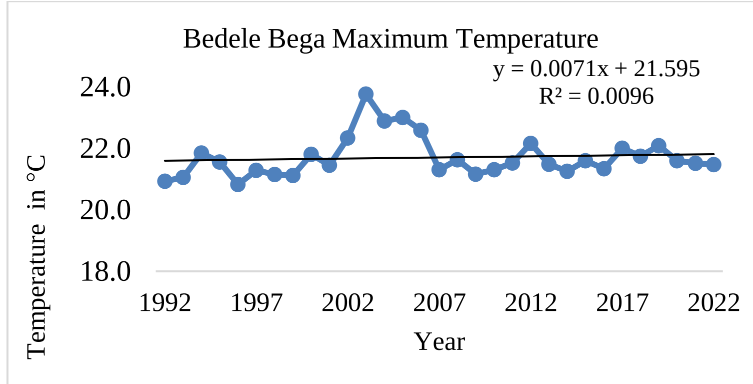

Figure 24: Bedele Bega maximum Temperature (1992-2022)

Effects of Climate Variability on Maize Yields

Analysis of correlation

The research examined the correlations between environmental factors and maize yield, revealing significant relationships (Table 8). The onset of the growing season (SOS) showed a weak negative correlation of -0.143 with maize yield, indicating that delayed starts can reduce yields. Similarly, the end-of-season (EOS) had a weak negative correlation of -0.164, suggesting that an early end may adversely affect yields. The length of the growing period (LGP) also exhibited a weak negative correlation of -0.213, implying that shorter growing periods are linked to decreased yields.

Temperature-related variables were notably impactful; the kremt mean maximum temperature (KTmax) had a strong positive correlation of 0.609 with maize yield, indicating that higher maximum temperatures enhance yields. Likewise, the kremt mean minimum temperature (KTmin) correlated positively at 0.554, suggesting that higher minimum temperatures benefit maize production. Conversely, Kremt rainfall (KRf) displayed a negative correlation of -0.661 with maize yield, indicating that increased rainfall may negatively affect production.

Table 8: Summary of Pearson Correlation

	Pearson Correlation						
	Yield	***SOS***	***EOS***	***LGP***	***KTmax***	***KTmin***	***KRf***
Yield	1	-0.143	-0.164	-0.213	0.609*	0.554*	-0.661**
SOS	-0.0143	1	-0.244	-0.777**	0.320	-0.223	-0.280
EOS	-0.164	-0.244	1	0.720**	-0.195	0.438	0.537*
LGP	-0.213	-0.777**	0.720**	1	-0.466	.222	0.605*
KTmax	0.609*	0.320	-0.195	-0.466	1	0.220	-0.578*
KTmin	0.554*	-0.223	0.438	0.222	0.220	1	0.027
KRf	-0.661**	-0.280	0.537*	0.605*	-0.578*	0.027	1

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

SOS=Season of start rain,EOS=End of rain season ,LGP=length of growing periods, KTmax= Kiremt maximum Temperature, KTmin = Kiremt Minimum Temperature, KRf= kiremt Rainfall

Regression analysis

This study used multiple regression analysis to examine the relationship between maize yield and climatic factors: Start of Season (SOS), End of Season (EOS), Length of Growing Period (LGP), Kiremt mean maximum (KTmax), and minimum temperatures (KTmin), and Kiremt rainfall (KRf) (Table 9). The regression model: **Yield = −261.45 −** 0.28SOS − 0.064EOS − 0.126LGP + 6.042KTmax + 17.384KTmin − 0.014KRf showed both the magnitude and direction of each variable's influence. SOS, EOS, and LGP had statistically insignificant negative effects on yield, with decreases of 0.280, 0.064, and 0.126 quintals/ha per unit increase, respectively. In contrast, KTmax and KTmin significantly increased yield by 6.042 and 17.384 quintals/ha, indicating a strong positive impact of temperature. However, KRf had a significant negative effect, reducing yield by 0.014 quintals/ha per mm increase, highlighting the adverse impact of excess rainfall.

Table 9: Coefficients of regression analyses for onset, kremt rain total and kremt average temperature at Bedele

Coefficients[a]						
Model		**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
		B	Std. Error	Beta		
1	(Constant)	-261.450	127.818	-	-2.045	0.075
	SOS	-0.280	0.192	-0.571	-1.456	0.183
	EOS	-0.064	0.162	0.149	0.392	0.705
	LGP	-0.126	0.166	-0.441	-0.758	0.470
	KTmax	6.042	4.838	0.224	1.249	0.025
	KTmin	17.384	7.604	0.424	2.286	0.052
	KRf	-0.014	0.005	-0.516	-2.635	0.030

a. Dependent Variable: Yield

The coefficient of determination (**R^2 = 0.864**) indicates that 86.4% of maize yield variation over the past 15 years is explained by climatic factors—SOS, EOS, LGP, Kiremt mean maximum and minimum temperatures and rainfall. The remaining 13.6% is due to non-climatic factors like soil properties, management, and inputs. The multiple correlation coefficient (**R = 0.929**) shows a strong positive linear relationship between these variables and maize yield (Table 10).

Table 10: Regression values for predictors

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.929[a]	0.86	0.762	4.1378

a. Predictors: (Constant), SOS EOS, LGP, KTmax, KTmin, KRf

The study found that maize yield had weak negative correlations with the start of season (SOS: -0.143), end of season (EOS: -0.164), and length of growing period (LGP: -0.213), suggesting delayed starts, early ends, or shorter seasons may reduce yields. In contrast, Kiremt mean maximum (KTmax: 0.609) and minimum temperatures (KTmin: 0.554) showed strong positive correlations, indicating that warmer temperatures enhance yield. However, Kiremt rainfall (KRf: -0.661) had a strong negative correlation, implying that excessive rainfall negatively affects maize production.

Climate variability adaptation strategies of the study area

Within the study area, the impact of adaptation strategies to climate variability has manifested across diverse demographic and socio-economic characteristics within the surveyed households. These pertinent factors are encapsulated in the following Table 11.

Table 11: Summary of demographic and socio-economic that affect adaptation strategies of climate variability in the study area

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Age	40.1	13.7	12.0	72.0
Education level of HH	4.0	4.0	0.0	12.0
Farm experiences	23.8	13.7	2.0	60.0
Total livestock	2.0	1.4	0.0	5.0
Farm income	7443.1	7285.3	1230.0	59650.0
Land size	5.3	3.9	0.0	10.1
Frequency of extension contact	4.8	6.0	0.0	21.0

The study analyzed demographic and socio-economic factors influencing climate variability adaptation strategies. The average age of participants was 40.1 years (SD = 13.7, range: 12–72), with household heads having a mean education of 4.0 years (SD = 4.0, range: 0–12). The average farming experience was 23.8 years (SD = 13.7, range: 2–60), and livestock ownership averaged 2.0 units (SD = 1.4, range: 0–5).

Farm income showed wide variation, averaging 7,443.1 (SD = 7,285.3, range: 1,230–59,650), while landholding averaged 5.3 hectares (SD = 3.9, range: 0–20.1). Extension contact frequency averaged 4.8 times (SD = 6.0, range: 0–21), reflecting varied access to agricultural advisory services.

Table 12: Summary of Institutional characteristics of the surveyed Households

Variables	Frequency	Percent
access to credit	75	51.72
not access to credit	70	48.28
trained to climate change	95	65.5
not trained to climate change	50	34.5

This study examines adaptation strategies to climate variability, highlighting factors influencing these strategies. Table 12 summarizes key findings: 75 households (51.72%) reported access to credit, while 70 (48.28%) did not. Additionally, 95 households (65.5%) received climate change training, compared to 50 households (34.48%) that did not. These factors provide valuable insights into climate adaptation strategies in the study area.

Adaptation strategies employed by sampled households

This research explores adaptation strategies to climate change, highlighting the various measures employed by farmers to mitigate its effects. Survey data from 145 households shows that common strategies include adopting improved crop varieties, adjusting planting dates, afforestation, crop diversification, and soil-water conservation (Table 13). Notably, many farmers use a combination of these strategies. Specifically, 96 households (66.21%) use improved crop varieties, 106 (73.1%) adjust planting dates, 109 (75.17%) practice tree planting, 81 (55.86%) diversify crops, 45 (31.03%) employ irrigation, and 116 (80%) utilize soil-water conservation.

Table 13: Summary of Adaptation strategies employed by sampled households

Variables	Responses	Frequency	Percentage
Using improved crop variety	Yes	96	66.21
Adjusting the plant date	Yes	106	73.10
plant trees	Yes	109	75.17
crop diversification	Yes	81	55.86
Applying irrigation	Yes	45	31.03
Soil-water conservation	Yes	116	80.00

Determinants of households' choice of climate variability adaptation strategies

This research examines adaptation strategies to climate change, revealing that farmers in the study area implement various measures to mitigate its effects. A survey of 145 households shows that these strategies include adopting improved crop varieties, adjusting planting dates, afforestation, crop diversification, and soil water conservation (Table 14). Many farmers employ a combination of these strategies, indicating a multifaceted approach to adaptation. The findings reveal that 96 households (66.21%) use improved crop varieties, 106 households (73.1%) adjust planting dates and 109 households (75.17%) practice tree planting. Crop diversification is adopted by 81 households (55.86%), while 45 households (31.03%) use irrigation techniques, and soil-water conservation is implemented by 116 households (80%).

The multivariate probit model results indicate the likelihood of households adopting various adaptation strategies: using crop varieties (66.2%), adjusting planting dates (73.1%), planting trees (75.2%), crop diversification (56.0%), applying irrigation (31.0%), and soil water conservation (SWC) (80.0%) (Table 13). Among these, the application of irrigation had the lowest likelihood at 31.0%, compared to other strategies. These findings suggest that different demographic and socioeconomic characteristics influence households' choices of adaptation strategies to climate variability. Out of ten identified factors affecting these decisions, three significantly influenced the use of crop varieties (education, farm income, extension contact), three affected planting date adjustments (total land size, extension contact, climate training), three influenced tree planting (total land size, education, access to credit), three impacted crop diversification (education, farm experience, extension contact), and three affected irrigation practices (education, extension contact, access to credit). Additionally, five factors significantly influenced soil water conservation: age, total land size, education, farm experience, and climate-related training (Table 14).

Table 14: Multivariate probit results for households' climate variability adaptation choice

	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
AGHH	0.007	0.017	0.017	0.018	-0.011	0.017	0.004	0.015	0.013	0.015	0.059***	0.018
SexHH	0.424	0.287	0.023	0.305	0.363	0.289	-0.114	0.275	0.420	0.317	-0.217	0.370
EDUHH	0.078**	0.039	0.036	0.038	0.066*	0.038	0.064*	0.033	0.064*	0.034	0.100**	0.044
FARMEXP	0.002	0.017	-0.025	0.018	0.017	0.017	0.025*	0.015	-0.018	0.015	-0.05***	0.018
TLHOLD	0.130	0.105	0.144	0.104	-0.150	0.098	0.048	0.094	0.141	0.097	-0.156	0.112
FARMINC	0.000***	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
LSHOLD	-0.031	0.031	0.068*	0.038	0.069*	0.035	0.007	0.031	-0.036	0.035	0.090**	0.043
EXTCONT	0.043*	0.025	0.049*	0.025	0.015	0.022	0.003	0.021	0.042**	0.021	0.001	0.025
ACCRDT	0.312	0.250	-0.338	0.257	-0.49*	0.254	-0.018	0.234	0.507**	0.250	-0.322	0.285
CCRTR	0.368	0.258	0.579**	0.262	0.215	0.276	0.454*	0.249	-0.071	0.277	0.903***	0.297
_cons	-1.61***	0.584	-0.402	0.534	0.236	0.502	-1.3***	0.496	-1.598***	0.519	-0.722*	0.590
Predicted probability	0.662		0.731		0.752		0.560		0.310		0. 80	

***, ** and * significant at 1%, 5% and 10% probability level respectively.

Conclusion and Recommendation

Conclusion

Overall, the study area experienced moderately variable monthly rainfall, indicating consistent precipitation critical for crop production. However, the Bega and Belg seasons were unreliable due to high rainfall dispersion, posing risks for rain-fed agriculture and planting dates. Kremt rainfall was reliable during the growing season, supporting crop production. The onset of the rainy season in April encourages land preparation for agriculture, while the end date in November aligns with harvesting times for some crops. The high number of rainy days corresponds with total annual rainfall and overall wetness in the area. The low variability in temperature suggests consistent climatic conditions; however, increased temperatures positively impact maize yields while rainfall events negatively affect them. Demographic and socio-economic factors significantly influence the choice of adaptation strategies to climate variability. Households in the study area predominantly practice soil water conservation as an adaptation measure, reflecting its emphasis in national policies to address climate variability effectively.

Recommendations

Based on the findings of this research, several recommendations are proposed to guide farmers, policymakers, and other stakeholders. Farmers are advised to prioritize the Kremt (main rainy season) rainfall for rain-fed agricultural activities, as it exhibits lower variability compared to other seasons. Agricultural policies should be aligned to support and enhance this seasonal focus. Although the region benefits from substantial annual and Kremt rainfall, the risk of floods and surface runoff remains significant; thus, establishing robust early warning systems for flood events is essential. It is recommended that farmers initiate planting between April 1 and April 27, capitalizing on the early onset of rainfall, and adjust their agricultural calendars accordingly, given that the rainy season typically concludes in November. Crop selection should be aligned with this seasonal pattern to ensure timely harvests. Furthermore, maintaining consistent soil moisture is critical, as most years exhibit moderate wetness, necessitating practices that conserve and enhance soil water retention. Finally, policymakers should design climate adaptation strategies that prioritize key socioeconomic factors such as educational attainment, farming experience, landholding size, household income, access to credit, and participation in climate-related training programs, to effectively mitigate the adverse impacts of climate variability.

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