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Characterizing Rainfall Variability to Enhance Agricultural Planning in the Eastern Oromia, Ethiopia

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Abstract

Rainfall variability is one of the major challenges for agriculture in Eastern Oromia, Ethiopia, where smallholder farmers rely mostly on rain-fed systems. This study investigates rainfall patterns, from 1992 to 2024, basically using the dataset from the Ethiopian Meteorological Institute. Rainfall trends and magnitudes were analyzed by using Mann-Kendall test and Sen's slope, while spatial trends were interpolated with inverse distance weighting in ArcGIS. Onset and cessation dates, the length of the growing period, and dry spells probabilities were examined using Markov chain modelling in INSTAT+. Results showed substantial variation in mean annual rainfall among woredas. Average annual precipitation ranged from 563.6 mm in Mieso to 886.4 mm in Chiro, this is may be largely influenced by local topography and other factors. The annual Precipitation Concentration Index (PCI) was 17.9 in Chiro while 19.8 was found in Babile, indicated a moderate concentration of rainfall. For the Kiremt season, the PCI values ranging from 31.6 in Babile to 37.4 in Chiro, reflecting strongly irregular rainfall distribution during study periods. During the Belg season, the

Precipitation Concentration Index values between 35.9 in Mieso to 39.8 in Gurawa, suggesting greater variability than Kiremt season. Onset and cessation date varied across the woredas. Late onset date was observed in the Mieso and Babile (80-90 days), but in Chiro early onset was observed (65-70 days), this shortened the growing periods to 65-81 days. Kiremt started early in Gurawa (150-160 days) and then ran late into Babile (170-180 days) with a stable end around mid-October (285-290 days), and the growing periods were 85-110 days. Dry spell probabilities show that Mieso and Babile are drought prone areas, during the whole study period. These results point toward the need for flexible measures like planting drought tolerant crops, adjusting sowing date, supplemental irrigation, and using soil conservation practices, so as to strengthen resilience in selected woredas of Eastern Oromia.

Keywords: Climate adaptation strategy, Dry spell length, Growing period, Rain-fed agriculture, Seasonal variability

1. INTRODUCTION

Rainfall variability is one of the major constraints to agricultural production in Ethiopia, particularly in Eastern Oromia where most farming is rain fed [1]. Agriculture is often described as the main pillar of Ethiopia's economy, it contributes approximately 34% to the national Gross Domestic Product (GDP) and providing employment for close to 80% of population [2, 3]. Despite its importance, the sector continues to face persistent challenges, including limited access to farming inputs, weak infrastructure, weak market linkages, and highly uneven and unpredictable rainfall patterns [4]. Among these, rainfall variability is the most critical factor, because it directly affects farm output, mainly in semi-arid, and sub-humid regions [5, 6]. The inconsistency in rainfall onset, cessation, and distributions, doesn't only reduces crop yields, but it further aggravates food insecurity, and it makes rural communities more exposed [7, 8]. Dealing this challenges requires understanding of rainfall variability and its implication for agricultural planning ([9]. Such knowledge can build adaptive strategies that boost resilience and support sustainable growth in Ethiopia's farming sectors [10].

Rainfall variability plays a significant role in shapping soil moisture conditions, which is strongly influence crop yields in Ethiopia [1,11]. The country has a lot of inconsistency in rainfall, varying across regions and seasons. This variability comes from atmospheric circulation setups, the way the Inter-Tropical Convergence Zone (ITCZ) is moving around, [12, 13] and Ethiopia's diverse topography and elevation [14].

The northward movement of ITCZ trigger the Belg rains running around February until May, then the Kiremt rains follow roughly from June to September. Also, there are factors like winds coming in from the Indian and Atlantic oceans, the tropical easterly jets and the Somali low-level jet, that all play into how rainfall ends up being distributed, so agriculture becomes vulnerable to climate changes [15, 16]. On a broader scale, Ethiopia's rainfall variability is influenced by global climate systems, and in particular the El Niño–Southern Oscillation (ENSO) and sea surface temperature anomalies in the Atlantic and Indian Oceans, as well as Pacific teleconnections [17. 18]. These shifts are particularly important during Kiremt season, when even minor shifts in rainfall can seriously affect agricultural productivity, and food security [19].

In Eastern Oromia, where farming is basically the core of people's livelihoods, the timing, intensity, and distribution of rainfall are critical factors for harvest outcomes, food security, and the resilience of farming households, [20]. The rainfall in the study areas are more erratic and highly variable, mainly due to climate change, land use change, and natural variability [21]. For agriculture planning to be effective in that kind of environment, it becomes important to understand rainfall variability more across both temporal and spatial scale [22].

A clear grasp of rainfall patterns not only vital for farmers sowing and harvesting, but it also gives policymakers and development practitioners valuable clues to ability more climate-smart interventions [23, 24].Therefore, analyzing rainfall variability is important for identification of key threats such as prolonged dry spell, flash floods, and drought conditions, and also informing appropriate response including crop diversification, water harvesting, and improved soil management practices [25, 26]. The diverse agro-ecological zones of Eastern Oromia, characterized by bimodal rainfall patterns [27].

The Belg rains run from February to May, and they're pushed by the northward movement of the Inter-Tropical Convergence Zone (ITCZ) [18], while Kiremt rains come roughly June through September, influenced by monsoon winds and atmospheric circulation [12] This variability, complicates agricultural planning but also creates room for tailored interventions [28]. Strengthen our grasp of how rainfall shift over time, can increase agricultural resilience, enhance food security, and encourage sustainable rural development across the region [29].

In earlier studies conducted in eastern and northern parts of Ethiopia, have mostly focused on seasonal rainfall variability and long term tendencies, with rarely looked at how these rainfall patterns can be integrated into agricultural planning. For example, [30] described the unpredictable Belg rains, and fluctuating year to year Kiremt rains in East Hararghe zone, with both often being influenced by El Niño and La Niña events. Similarly, [31] found, similar patterns in the North Shoa zone where rainfall variability is tied to broad climate influences worldwide.

However, this study is quite localized and do not adequately link rainfall characterization with agricultural planning. This leaves, a noticeable gap remains, in understanding of how rainfall information can actually guide farmers decision-making and support policy development. Integrate rainfall characterization into agricultural planning strategies, is therefore crucial to ensure that scientific insights somehow become achievable actions for resilience and food security. This study adopts a holistic approach to describing the rainfall variability across the selected woredas of Eastern Oromia region and seeks to link these results directly to agricultural planning strategies. In doing so, it combines climatological analysis together with agricultural planning perspectives, so it seeks to bridges the gap between scientific data and actual, real-world use. Finally, this study aims to characterize rainfall variability, and guide for agricultural planning in Eastern Oromia, Ethiopia, offering insights that support climate smart strategies, improve resilience, and strengthen food security in the region.

2.Material and method

2.1. Description of study area

The study was conducted in selected districts of East and West Hararghe Zones, Oromia, Ethiopia. These zones include diverse agro-ecological regions: lowlands (30–40%), midlands (35–45%), and highlands (15–20%). Altitudes range from 1,200 to 3,106 meters above sea level, shaping local climate conditions [32]. Average annual maximum and minimum temperatures are 24.7 °C and 11.5 °C, with mean rainfall around 790 mm [33]. Rainfall occurs mainly in Belg (February–May) and Kiremt (June–September), though Belg is less reliable [34]. The Kiremt season provides the bulk of annual rainfall, peaking in June–August before declining in mid-September, while Belg season from February to May), agriculture is predominantly mixed farming, combining

crops and livestock [35]. Farmers cultivate sorghum, maize, legumes, wheat, oilseeds, vegetables, and fruits [36]. Coffee (Coffea arabica L.) and khat (Catha edulis (Vahl) Forssk.) serve as key cash crops, while livestock such as cattle, goats, sheep, and donkeys provide draft power, manure, and income [37].

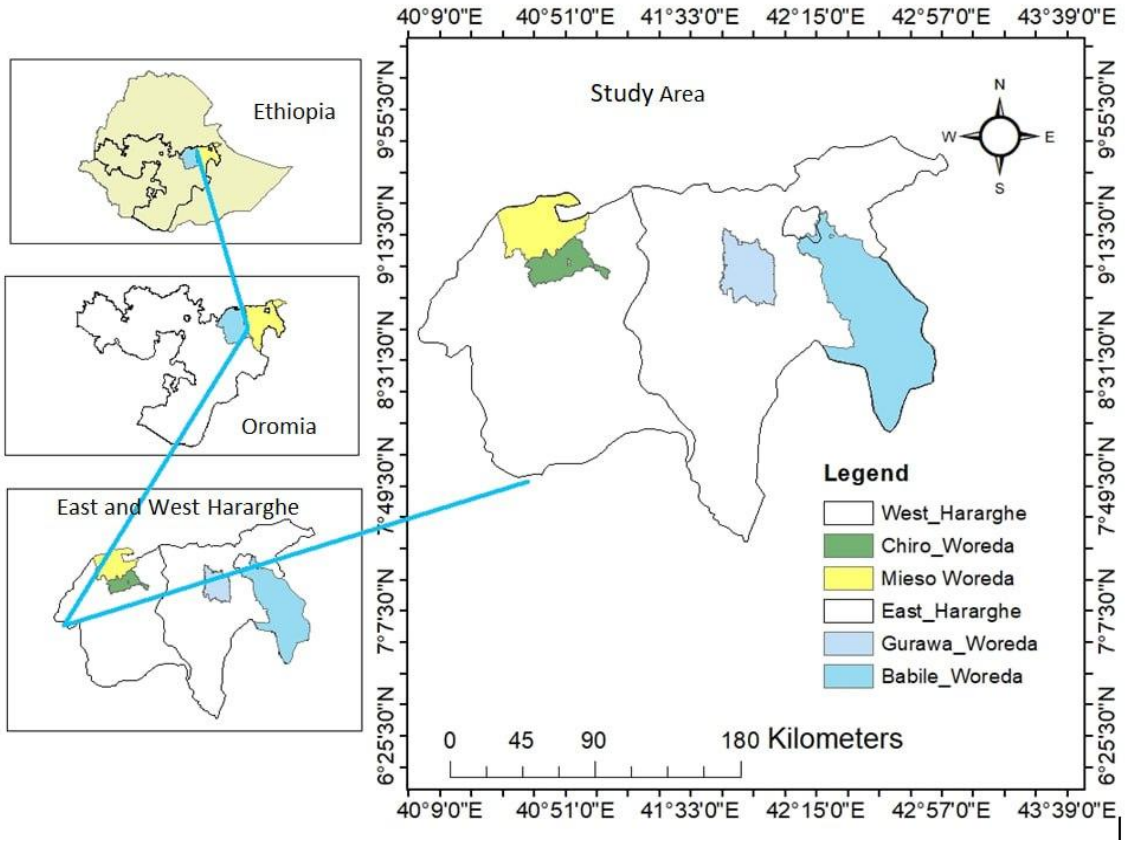


Figure 1. Location of the study area within Ethiopia, showing the Oromia region and the East and West Hararghe zones. The inset maps illustrate Ethiopia, Oromia, and the Hararghe zones, while the main map highlights the selected woredas (Mieso, Chiro, Gurawa, and Babile) with distinct colors. Coordinate grids, scale bar, and compass rose provide spatial reference, situating the study area within its broader administrative and geographic context

Table 1: Geographic and climatic characteristics of selected districts in East and West Hararghe Zones, Oromia (1992–2024)

No	Woredas	Latitude (°N)	Longitude (°E)	Elevation (m.a.s.l)	Periods
1	**Mieso**	9.2	40.8	1331	1992-2024
2	**Chiro**	9.1	40.9	1784	1992-2024
3	**Gurawa**	9.1	41.8	2460	1992-2024
4	**Babile**	9.1	42.2	1646	1992-2024

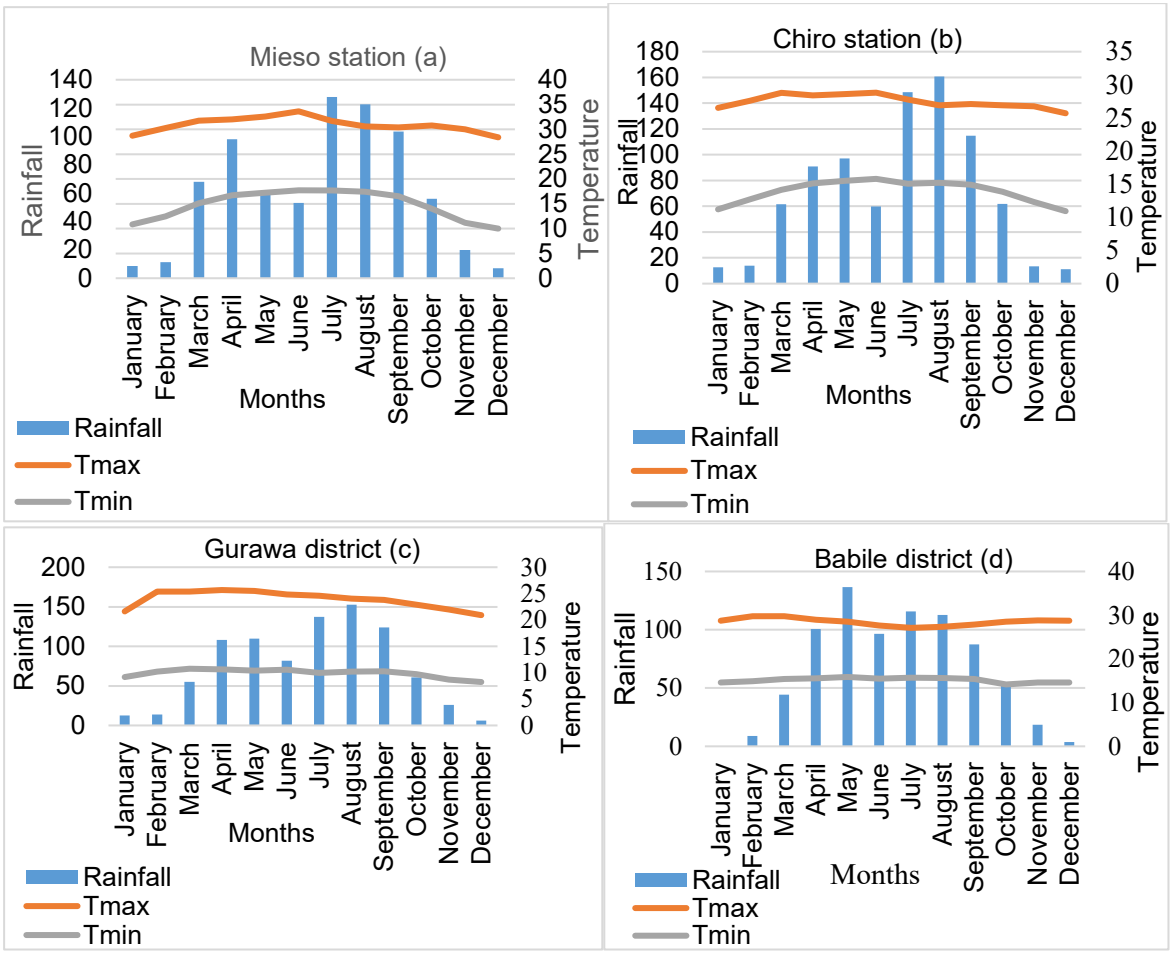


Figure 2 (a–d). Monthly annual rainfall and temperature distribution in Mieso, Chiro, Gurawa, and Babile stations, respectively (1992–2024). Blue bars represent annual rainfall (mm), while orange and gray lines show maximum and minimum temperatures (°C). Rainfall peaks in July and August during the Kiremt season, which is critical for crop growth. Belg rains (February–May) are limited and erratic, making them unreliable for early planting.

2.2. Source of data

Daily rainfall data were collected from the Ethiopian Meteorological Institute for the span between 1992 and 2024, focusing on stations that are within the study area boundaries. Then we sort of summarized the data into daily, monthly, seasonal, and annual means plus totals, which made it possible to inspect variability and direction changes across different time windows. For dealing with any missing records, we used the gridded dataset (4 * 4 km) that is provided via the Ethiopian Meteorological Institute's Enhancing National Climate Services, the ENCTS initiative (https://iri.columbia.edu/resources/enacts/). For generating rainfall surfaces at seasonal and yearly scales, we used the Inverse Distance Weighted (IDW)

interpolation approach (Shepard, 1968) in ArcGIS. Essentially, this technique predicts values at locations where we did not sample, by using the observed data and assigning influence based on how far each point is, [38]. Unlike more complex procedures like kriging, Inverse Distance Weighting (IDW) is kind of simple, it does involve assumptions about the statistical dataset.

2.3. Data quality control

Climate data sets often come with irregular or extreme values, that end up biasing statistical analysis. So to decrease those distortions, and still get results that stay stable over time, it helps to a careful process of spotting and removing outliers before starting the time series analysis [39]. In this study, we used the interquartile range (IQR) approach to point out and discard odd entries from the dataset, somewhat like a quick sift. This part helped make the next analyses more reliable, so the findings stay robust and dependable too [40]. The data range expressed by (1)

$$[\mathbf{Q1} - \mathbf{1.5} * \mathbf{IQR}, \mathbf{Q3} + \mathbf{1.5} * \mathbf{IQR}] \quad \textbf{(1)}$$

Q1 and Q3 are the lower and upper quartiles, respectively, and the IQR is basically just the difference between the two values. For spotting outliers, we usually rely on the rule that takes 1.5 times the IQR, but pushed beyond the quartile range. If an observation shows up under Q 1 − 1.5 × $I\ Q\ R$, or it goes beyond Q 3 + 1.5 × $I\ Q\ R$, then it gets flagged as an outlier [41]. Honestly this approach is important to gather extreme values in rainfall data, which in turn helps keep the time series inputs more refined and dependable. To detect outliers, this study used a threshold based strategy fixed in the Interquartile Range (IQR), drawing on [42] as shown in Equation (2) just below

$$\mathbf{Threshhold} = \mathbf{Q3} + (\mathbf{3} * \mathbf{IQR}) \quad \textbf{(2)}$$

2.4. Data Analysis

2.4.1. Trend analysis

The Mann-Kendall test is a well-known, non-parametric statistical approach used to spot monotonic trend in time-series data. It's especially useful for finding any long range shifts in hydrological and climatological variables, without needing to assume how the observations are distributed. In that way it gives dependable signal for whether a monotonic trend is increasing, decreasing, or maybe not present at all [43, 44]. So it

becomes a strong option for rainfall and temperature studies, since variability is common and the data often behaves non-normal.

Test statistics (S) sum of all the signs:

$$\mathbf{S} = \sum_{\mathbf{k=1}}^{\mathbf{n-1}} \sum_{\mathbf{j=k+1}}^{\mathbf{n}} \mathbf{sign(xj + xi)} \qquad (\mathbf{3})$$

In this study the trend test was used on the time series Xi, but first they were arranged by order for i=1, 2, …, n−1, and then on Xj, ranked from j=i+1, 2, …, n. Each observed value xi became the sort of anchor, and then it was confronted against the later data points Xj to see whether any upward or downward trend could be detected in the set of numbers. So that equation (2):

$$\mathbf{Sign(xj - xi)} = \begin{cases} \mathbf{1\ if\ (xj - xi) > 0} \\ \mathbf{-1 if\ (xj - xi) < 0} \\ \mathbf{0\ if (xj - xi) = 0} \end{cases} \qquad (\mathbf{4})$$

Where Xi and Xj stand for the annual values in year i and j (with j > i), the trend check interprets that if the amount of observations goes beyond 10 (n>10), then the test statistic S comes out as approximately normal, with mean E(S)=0. In that situation, the variance of the statistic is given by equation (5). Because of that, the variance of the statistic is stated in equation (5).

$$\mathbf{Var(s)} = \frac{\mathbf{n(n-1)(2n+5)} - \sum_{\mathbf{i=1}}^{\mathbf{m}} \mathbf{ti(ti-1)(2ti+5)}}{\mathbf{18}} \qquad (\mathbf{5})$$

Where n is that overall amount of observations and t i stands for the sample values of the time series, the test statistic Zs kind of is written like this: For n > 10, Zs ends up approximating the standard normal distribution and it gets calculated using the equation provided.

$$Zs = \begin{cases} \dfrac{\mathbf{s-1}}{\sqrt{\mathbf{var\ (s)}}}\ \mathbf{if\ s > 0} \\ \dfrac{\mathbf{s+1}}{\sqrt{\mathbf{var\ (s)}}}\ \mathbf{if\ s < 0} \\ \dfrac{\mathbf{s-1}}{\mathbf{var\ (s)}}\ \mathbf{if\ s = 0} \end{cases} \qquad (\mathbf{6})$$

Zs is the standardized test statistic used to determine significance. Because Zs follows a normal distribution, significance can be tested at chosen confidence levels, such as 95%.

2.4.2. Rainfall onset (SOS), Cessation date (EOS), and the Length of the Growing Period (LGP)

To find onset and cessation date, we used the method suggested by [45] which has been widely used for Africa [46] Since farmers usually limit planting to the months when rain is more or less expected, we define the Belg period as February to May, and the Kiremt period as June to September when we calculating the cessation dates [47, 48]. Seasonal rainfall should be higher than the long term mean, and in our study we used a 32-year baseline to set that threshold [45]

Onset defined as the first day when rainfall reaches 20 mm across three consequative days, as long as that stretch is not then followed by a dry spell that lasts more than 10 days during the next 30 days. It should occur an earliest starting day of February 1 for Belg and June 1 for Kiremt season, while for cessation date May 1-30 for Belg and September 1-30 for Kiremt season, when the capacities of soils to persist precipitation with a water balance equal to zero is 100 mm [49]. The first date on which soil moisture is fully depleted and negligible for plant growth is cessation date. Length of growing period was measured by the difference between onset date and cessation date of rainfall.

2.4.3. Analysis of probability of dry spell length

Daily rain records from Mieso, Chiro, Gurawa, and Babile stations were gathered and processed using INSTAT+ (Version 3.37) together with a Markov Chain model. The Markov Chain method was used because it can allow rainfall occurrence as a probabilistic process, where the chance of rain on a given day depends on if the day before was wet or dry. makes useful for analyzing long dry or wet spells, estimating the probability of consecutive dry days, and identifying rainfall patterns that are important for agricultural planning.

2.5. Assessment of Rainfall Variability

2.5.1. Coefficient of variations (CV)

The coefficient of variation, CV, is one of those useful statistics that helps rainfall variability. If the CV comes in under about 20%, it usually points to low variability. When

the CV values ranging between 20% and 30% it suggests moderate variability, whereas if the values are more than 30% to 40% then variability is considered high. If the CV goes beyond 40% to 70%, then we are basically dealing with very high variability, and anything above 70% is treated as extremely high [50]. This method of grouping rainfall variability is widely applied in climatology. It is computed as:

$$\mathbf{CV} = \frac{\boldsymbol{\sigma}}{\boldsymbol{\mu}} * \mathbf{100} \qquad (7)$$

Where CV stands for the coefficient of variation, σ indicates the standard deviation, and μ represents the annual mean precipitation.

2.5.2. Precipitation Concentration Index (PCI)

It is statistical measure used to check how rainfall is spread across the months in just one year. This kind of method, helps see if the precipitation is rather evenly distributed, or if it clusters up within a limited time window. [51] says that when the PCI is under 10, it points to a fairly uniform monthly pattern for rainfall. If the PCI ranging 11 to 20 moderate build up, and when it goes above 20 that suggests strong irregularity, most rainfall displays up in just a few months. This classification gives a workable framework to judge rainfall variability, which is important for making sense of climate behavior, scheduling farming tasks, and managing the crop water needs. Overall this way of classifying things feels practical for judging how variable rainfall is, which matters when trying to understand climate behavior and also when planning agriculture, and what to do with crops.

$$\mathbf{PCI} = \frac{\sum_{\mathbf{t-1}}^{\mathbf{12}} \mathbf{Pi^2}}{(\sum_{\mathbf{t-1}}^{\mathbf{12}} \mathbf{Pi})^2} * \mathbf{100} \qquad (8)$$

2.5.3. Rainfall Anomaly Index (RAI)

The Rainfall Anomaly Index (RAI), first introduced by Van Rooy in 1965, has become go-to drought indicators. It basically works by taking annual or seasonal precipitation and then comparing it up against long-term historical trend. Once you normalize those rainfall numbers, the RAI makes it easier to see if a given year is actually wet, dry, or stuck in that middle zone. When the index comes out positive, that usually means wet conditions are happening, while negative values point toward

dryness. To figure out the RAI, we do basically take the mean of the ten wettest years plus the ten driest years, and then we use certain limits so it's possible to tell apart moderate wiggles from extreme anomalies. This makes the whole method feel standardized and dependable, like a practical instrument for tracking droughts and also supporting farm decisions.

$$\mathbf{RAI} = \frac{\mathbf{Pt} - \mathbf{Pm}}{\boldsymbol{\sigma}} \qquad (\mathbf{9})$$

Where Pt= rainfall in the year or season of interest, Pm=long-term mean rainfall, σ =standard deviation of rainfall over the reference period.

Table 2: Classification of Rainfall Anomaly Index (RAI) values into wet or dry categories

RAI	Description
≥3.0	Extremely wet
2.00-2.99	Very wet
1.00-1.99	Moderately wet
0.50-0.99	Slightly wet
-0.49 - +0.4.99	Near normal
-0.50 to -0.99	Slightly dry
-1.00 to -1.99	Moderate dry
-2.00 to -2.99	Very dry
≤-3.00	Extremely dry

(Source, [52])

Table 2 classified the Rainfall Anomaly Index (RAI) values into wet and dry categories. Positive RAI values indicate wet conditions, while negative values represent dry conditions. This classification provides a standardized framework for interpreting rainfall variability and identifying periods of above-average or below-average rainfall, supporting analysis of climatic trends and agricultural planning.

3. RESULT AND DISCUSSION

3.1. Mean annual rainfall distribution, variability, and trends

Over the last 32 years, the mean annual rainfall in selected woredas has shown clear spatial differences, with patterns that felt erratic, and also fluctuating throughout the study periods. At the Mieso station, the mean rainfall was 563.8 mm, while the interpolated values were from 398.1 up to 797.8 mm, which really points to the most variability in annual rainfall. Chiro actually stood out, with the highest average at 886.0 mm, and the interpolated values were between 582.7 and 886.1 mm, so it is basically a wetter landscape. Gurawa recorded an average of 733.5 mm, with interpolated

values from 592.4 to 860.0 mm, indicating moderate variability. In a sense rainfall here is usually higher than Mieso but, lower than Chiro.

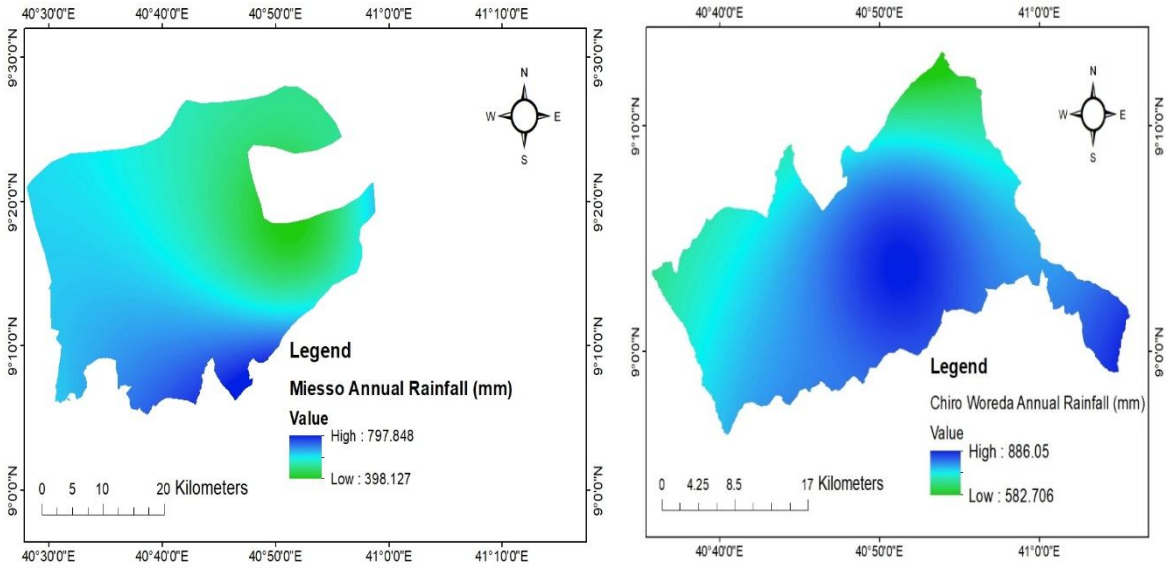
This variation may be Ethiopia's rainfall is highly varied, even across short distances, due to complex interactions between the Intertropical Convergence Zone (ITCZ), monsoon flows, and local geography of the study woredas. Chiro and Gurawa placed at high altitude as compared to Mieso and Babile woredas. This altitude makes gain rainfall from orographic lifting. Meanwhile the lower-altitude Mieso and Babile areas get dry winds, reduced moisture, and the rainfall becomes less predictable. The results align with the research conducted Tesfaye et al. (2019) [53] reported that Ethiopia's rainfall variability is shaped by ITCZ shifts and monsoon flows**,** interacting with local geography to produce sharp differences even across short distances. Similarly, [54], emphasize that elevation, together with localized weather driver's shapes rainfall distribution in eastern Ethiopia.

Rainfall variability across the woredas confirms the distribution of rainfall. Chiro (19.4%), and Gurawa (22.7%) indicate moderate variability. In contrast, Mieso (34.4%) and Babile (33.6%), reflecting high variability of rainfall, with stronger fluctuation from year to year compared to the other woredas. This disparity shows that the highland regions get more reliable rainfall, while the lowland districts keep dealing with uncertainty, so their rain- fed agriculture exposed rainfall variability. The study woreda is fragmented land, with land degradation and deforestation reducing vegetation and soil fertility. These changes increase rainfall variability and reduce farming productivity and resilience in the study areas.

The high variability of mean rainfall in Babile and Mieso, elevates the risk for crop failures, delayed planting, and lower harvests. Adaptation strategies like water harvesting, drought tolerant crops, and supplemental irrigation are crucial for Babile and Mieso woredas. In contrast, the moderate variability in Gurawa and Chiro, seems to allow for more reliable for sowing date planning and harvesting time. The results are important because they give district-level perspective on rainfall variability, offering useful direction for both smallholder farmers, and policymakers. The Findings correspond to with [27] described, highland areas receive moderate rainfall variability. Meanwhile, the lowland plus midland zones keep showing high variability, usually over 30% throughout the year.

Trend analysis showed a slight lift in rainfall for Gurawa, coming in at 9.6 mm per year. On the other hand, Mieso had a drop of 1.7 mm per year, and Chiro and Babile had small declines around 0.48 mm and 0.51 mm per year respectively. But not statistically significant, $P<0.05$ (Table 3). The Z statistics pointed to some spatial variation, Gurawa and Chiro were the wetter ones, while Mieso and Babile were drier during the study periods (Table 3).

Decreasing or increasing rainfall in the highland and lowland areas affects farming system. This spatial variability affects farming systems: in the highlands can support moisture demanding crops, while lowland like Mieso and Babile need drought tolerant crops, soil conservation, and water harvesting. These results line up with [55] reported annual rainfall looks like it is dropping, though in some years it was not always statistically significant. The declines stronger in lowland zones, reflecting spatial variability across the region. In a similar vein, [54] stressed that elevation along with nearby atmospheric drivers has a decisive influence on how rainfall falls into place, especially in eastern Ethiopia.



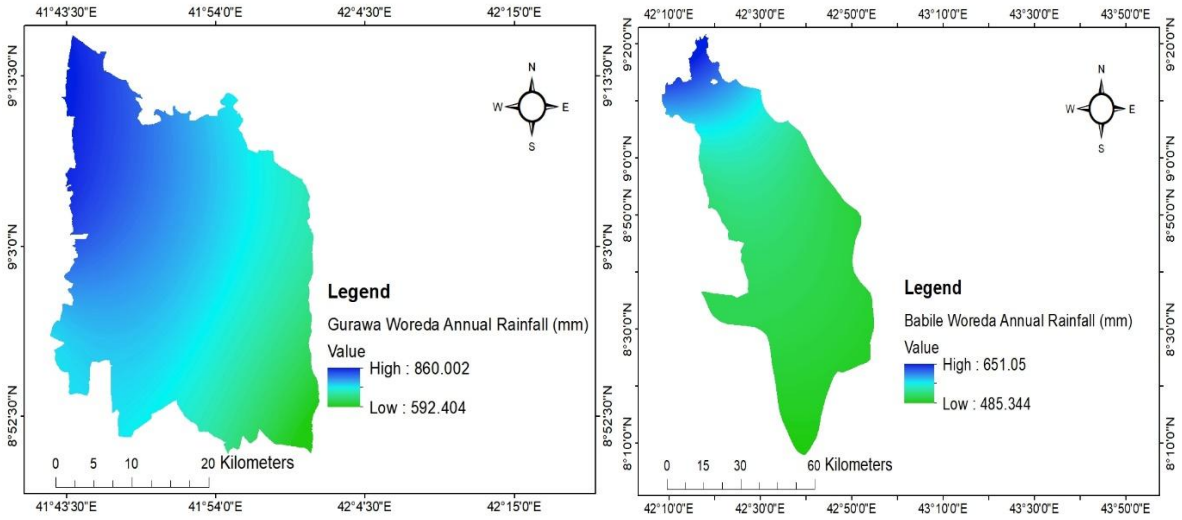


Figure 3 (a–d). Spatial distribution of annual rainfall (mm) nearby Mieso, Chiro, Gurawa, and Babile Woreda, stations generated using ArcGIS with the Inverse Distance Weighting (IDW) interpolation technique from meteorological station records. The map reveals that rainfall is not evenly distributed; some zones experience relatively higher precipitation (blue shades), while others are drier (green shades). This spatial heterogeneity is critical for agricultural planning, water resource management, and climate adaptation strategies. The inclusion of geographic coordinates, a north arrow, and a scale bar enhances the map's utility for spatial analysis and comparison.

3.2. Kiremt season (summer) (June–September) rainfall variability and agricultural implication in the Study areas (1992-2024)

The Kiremt season, which runs from June to September, is like the main rainy season in Eastern Oromia, and it really helps smallholder agriculture in the areas. The results presented in Figures 4a-d and Table 4, show clearly how Kiremt (summer) rainfall changes across the selected woredas. For instance, Mieso 317.5 mm, and the interpolated figures go from 210.8 to 429.1 mm. This broad variability shows in general lower rainfall; it confirms the drier conditions of Mieso woreda. Meanwhile, Chiro had a mean rainfall amount of 447.4 mm, with interpolated values that received between 313.7 and 477.5 mm. The minimum and maximum figures, here, are higher than in other woredas, indicates Chiro looks consistently wetter. On the other hand, Gurawa's average rainfall was 340.5 mm, and the interpolated range ran from 266.7 to 444.7 mm. This shows moderate rainfall, higher than Mieso but also lower than Chiro, with a fairly dependable distribution.

Babile on the other hand had mean rainfall of only 93.7 mm, and the interpolated values go from 168.4 up to 328.2 mm. So the station mean is noticeably lower than those interpolated numbers, it suggests localized dryness and, maybe an underestimation by the station compared to what's around it. These differences may be due to the geography and the altitude of the study areas that influence the way rainfall gets distributed, and that then affects agricultural planning, and food security as well. Rainfall variability also brings out the contrast between woredas: Mieso (CV 20.6%, SD 65.5 mm) and Chiro (CV 27.7%, SD 132.2 mm) showed the most dependable rainfall, though Gurawa (CV 36.4%, SD 124.1 mm) and Babile (CV 37.06%, SD 34.7 mm) had higher uncertainty across the study periods.

The spatial difference shows that the central and western sections of each woreda, shown with deep green shading in Figures 4a-d, get the most precipitation. This likes to be linked to the northward shift of the Inter-Tropical Convergence Zone (ITCZ). On the other hand, the eastern and southern areas experience rather low Kiremt rainfall, and that pattern is formed by how close they are to arid lowlands, and the windward influence coming from orographic highland ridges. This may be in the study areas farmland is fragmented have pushed farmer toward more intensive form of cultivation. Also, deforestation and city expansion can remain the local climate, by making surface temperatures increase and disturbing moisture recycling, which may affect the Kiremt rainfall patterns.

This observation is supported by [1], who mentioned that shifts in land use like forest clearing, pushing out built-up areas, and ramping up agriculture can really change local microclimates and disturb the way rainfall is set up. Yet, there are also natural drivers, for example fluctuates in the El Niño Southern Oscillation (ENSO), especially when La Niña shows up, which matter a lot for how Ethiopia's seasonal rainfall behaves. In some cases, these changes strengthen the monsoon winds and move the Inter-Tropical Convergence Zones (ITCZ) around, and that usually means the timing and presence of seasonal showers. These findings provide valuable climate insight for both small holder farmers and policy makers, helping guide agriculture decisions and adaptation planning.

The trend analysis of Kiremt rainfall in Eastern Oromia has come out with a mixed result across different districts, pointing to that area's spatial variability. In particular, Mieso (β = -0.015 mm/year) and Babile (β = –0.24 mm/year) are showing a declines,

which is not statistically significant ($p > 0.05$). It reflects indicates that those areas can be more prone to recurrent droughts.

In contrast, Chiro (1.65 mm/year) and Gurawa (3.75 mm/year) seem to be showing a bit of an upward trend, statistically insignificant ($P > 0.05$). That kind of stability might lead to giving a more stable for agricultural planning especially against the more obvious fluctuation in Mieso and Babile. These observations align with the earlier research by [56], which mentioned mixed rainfall trends and a growing level of variability across Eastern Ethiopia. Similar points were also repeated by [57], they found that in most stations the downward trends were statistically non-significant, except for Kobo and Alamata station.

These declines were tied to the ongoing droughts and the vulnerabilities that become evident in lowland places, and this indicates the broader story of climate pressures challenging Ethiopia's lowland farming systems. In the East and West Hararghe Zones, smallholder farmers depend on Kiremt rainfall, which is crucial, sustaining agricultural production and ensuring the constancy of staple crops such as sorghum, maize, teff, wheat, and barley. So, taking all this into account, it seems obvious that local adaptation strategies are needed to handle climate variability.

In Gurawa and Chiro, the stable rainfall helps manage natural flooding, which lowers the chances of soil erosion, waterlogging, and damage to crops. In parallel, Mieso and Babile are dealing with harsher conditions, so they really need more targeted responses, such as drought tolerant crops, early maturing varieties, and practical water harvesting approaches.

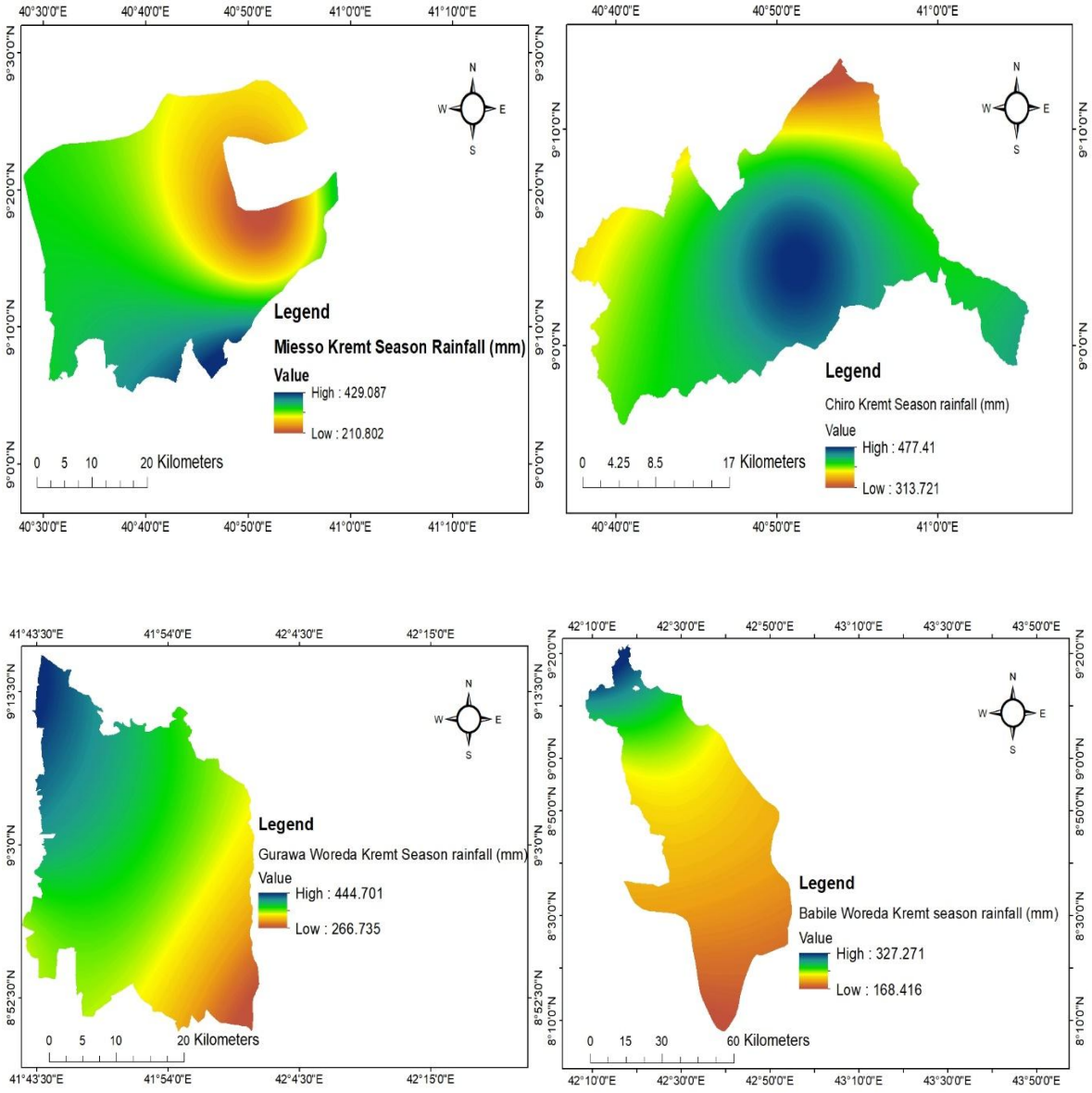


Figure 4 (a–d) Kiremt (summer) rainfall distribution across Mieso, Chiro, Gurawa, and Babile districts (1992–2024). Panels depict the variability of seasonal rainfall during the Kiremt period. The highest rainfall was recorded in Chiro (477.41 mm) and Gurawa (444.7 mm), while the lowest values were observed in Babile (327.2 mm) and Mieso. Gurawa exhibited intermediate variability, ranging from 444.7 mm to 266.7 mm. Spatial patterns show a decreasing rainfall tendency toward Babile, whereas Chiro and Gurawa maintain relatively higher and more stable rainfall regimes. Deep green shading indicates areas of high Kiremt rainfall, light green represents medium rainfall zones, and dark orange highlights regions with low rainfall distribution.

3.3. Belg season (February to May) rainfall distribution and variability and implication of agriculture

The figures (5a-d) below show how Belg rainfall is spread across Mieso, Chiro, Gurawa, and Babile woredas. For example, the mean rainfall in Mieso is about 177.7 mm. Meanwhile Chiro, Gurawa, and Babile reach 299.4 mm, 295.5 mm, and 191 mm, respectively (Table 3). Interpolated values are significantly varying from 160.5 to 273.2 mm in Mieso, then 213.6 to 313.3 mm for Chiro, 243.5 to 330.8 mm for Gurawa, and finally 215.1 to 234.6 mm for Babile.

The variability is apparent, as revealed in the coefficient of variations of: Mieso (36.6%, SD 68.2 mm), Chiro (33.5%, SD 100.3 mm), Gurawa (40.9%, SD 121.06 mm), and Babile (35.3%, SD 67.5 mm), indicating unstable rainfall patterns compared to Kiremt season. The high standard deviations between 75.6 and 96.7 mm across all woredas point to a higher variability than in the Kiremt season, and it really stresses how unpredictable Belg rainfall is in these places during the study periods (Table 3). This variation may be due to layered interaction of microclimate location and landscape of the study areas.

The study areas varied land scape with its highlands, plateaus and lowland plains, basically drives local weather and rainfall trends. Highland woredas benefit from orographic uplift that improves rainfall, while lowland areas, situated in moist air regions, experienced lower Belg season rainfall and greater exposure to dry conditions. In line with this, earlier research by [53, 58] has connected Belg rainfall variability to higher climate influences such as ENSO and the Somali Jet, showing how easily this region responds to large scale circulation patterns. Their results imply that Belg rainfall is not merely a local concern, it also ties into wider atmospheric circulation trends, making this season.

Erratic Belg rains, undermine sorghum and maize yields, with a shorter growing season and increase dry spells that ramp up the chance of crop failure in the study areas. Similarly, [59] reported that late and erratic Belg rains led to suppressed crop growth and Belg crop failure, particularly affecting sorghum and maize which is long cycle crop. In line with above results, [60] reported that shortened growing seasons and poor rainfall distribution caused food insecurity outcomes. Small holder farmers adopt drought-resistant variety, early maturing, earl, diversify crops, and invest in water harvesting to overcome the erratic Belg rains.

The trend results show a downwards pattern for Belg rainfall across Mieso, Chiro, Gurawa and Babile woredas, with slopes between -0.95 and 0.011 mm/year, but the change are not really statistically significant at p value is > 0.0.5, this result reflects

inconsistent Belg rainfall in the study areas was observed during study periods. Similarly, found that Belg rainfall in Ethiopia's northern highlands shows a statistically significant *decreasing trend*, contrasting with the main Kiremt season which exhibited an increasing trend. This decline in Belg rains has direct implications for crop production and food security in Belg-dependent areas. In align with above results, [62] reported Belg rainfall indicated a declining tendency in several regions, though not always statistically significant.

Most of the variability seems tied to the shifting of bigger climate mechanisms, including the Inter-Tropical Convergence Zone (ITCZ) moves, plus the ups and downs of the Indian Ocean Monsoon, and also Ethiopia's rugged and complicated terrain. Belg rainfall itself start from February to May, but it is high variable to anticipate, so it makes farming choices difficult, and it also adds higher chances of crop failure and food insecurity, especially in Mieso and Babile. So, adaptation strategies: farmers are encouraged to switch toward drought tolerant crops like sorghum and millet, do soil and moisture conservation, and start using water harvesting practices. They can build small ponds, and also use agronomic options such as early sowing, irrigation, and timely weeding. important for improving resilience to Belg rainfall fluctuates, and for protecting smallholder livelihoods in the affected woredas.

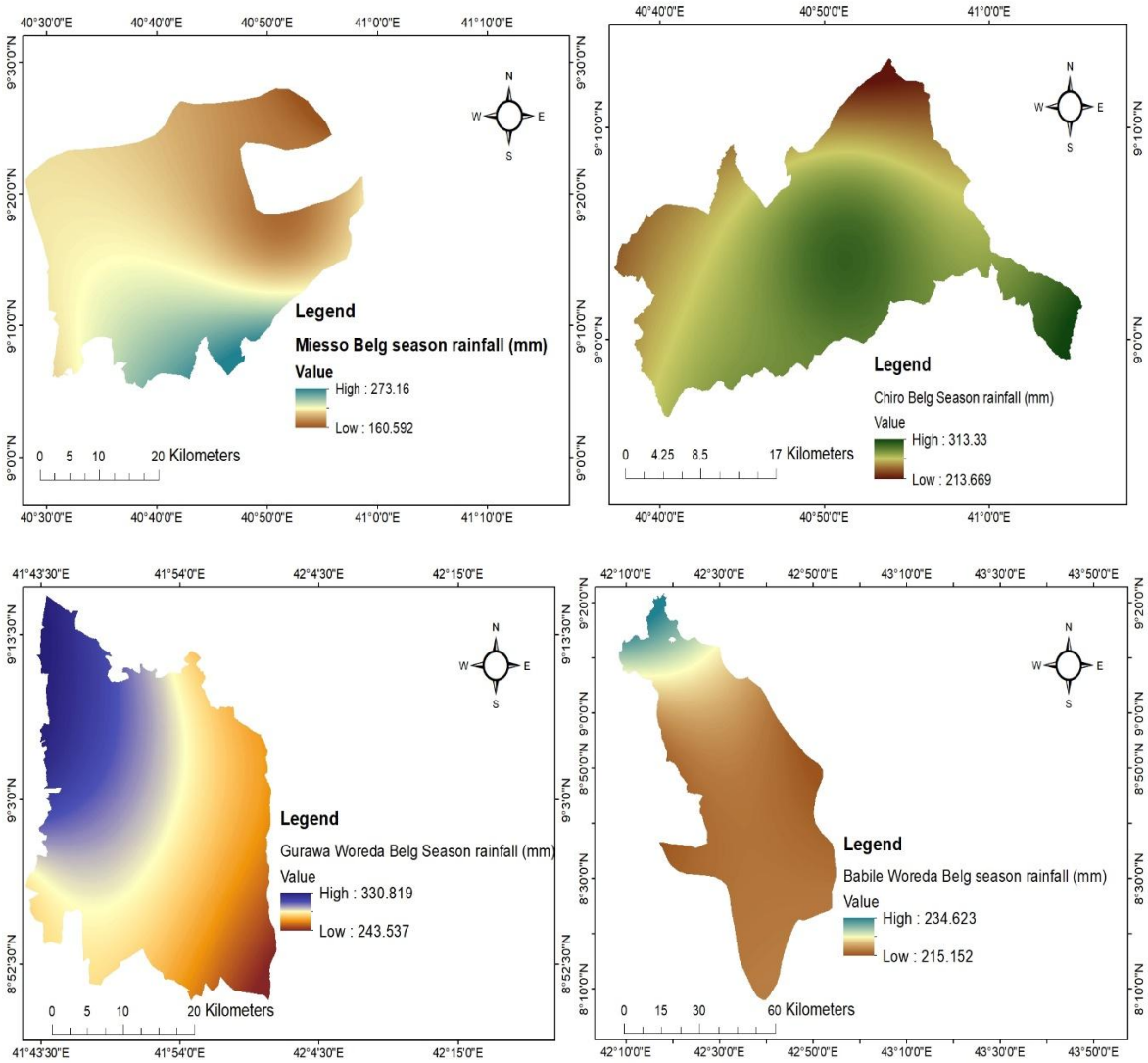


Figure 5 (a–d). Belg (spring) rainfall distribution across Mieso, Chiro, Gurawa, and Babile districts (1992–2024). Panels illustrate the variability of Belg rainfall totals. The highest rainfall was recorded in Gurawa (330.8 mm) and Chiro (313.1 mm), while the lowest values were observed in Mieso (140.5 mm) and Babile (215.5 mm). Seasonal ranges include Mieso (273.1–140.5 mm), Chiro (313.1–213.4 mm), Gurawa (330.8–243.5 mm), and Babile (234.6–215.5 mm). Spatial patterns show deep green shading for high Belg rainfall zones, light green for medium rainfall areas, and dark orange for low rainfall distribution.

3.4. Bega season (October-January) rainfall (1992-2024)

In the lowlands of East and West Hararghe, the Bega season, which is October–January, rainfall plays a crucial role for pastoralist communities. During this dry stretch, the rains help pasture regeneration and recharge groundwater.

From the analysis, the mean rainfall amount to be 68.6 mm, 109.18 mm, 97.2 mm, and 98.2 mm for Mieso, Chiro, Gurawa, and Babile respectively. The interpolated

values indicate Mieso had values between 15.56 and 95.9 mm, Chiro ranged from 55.3 up to 122.3 mm, Gurawa ranged between 92.7 and 108.03 mm, and Babile ranged 77.02 to 99.07 mm (Table 3, Figure 4). This finding point out clear spatial variability among woredas., Mieso shows the lowest rainfall and the most erratic behavior, meaning it can be hit harder by drought spells. These variations, important for rainfall assessments, since averages alone can mask key intra-district changes that influence crop choices, planting schedules, and risk-management planning.

Rainfall variability was especially high, with coefficients of variation from 44.4% up to 68.8%, and it suggests strong unpredictability across the 1992–2024. The standard deviation: Chiro (52.03 mm) and Babile (50.8 mm) having stronger dispersions than Gurawa (43.1 mm) and Mieso (45.8 mm) (Table 3). The Bega rainfall variability shows uneven, which makes planning for agriculture and managing resources more complex compared with other seasons across the districts.

The trend of Bega season rainfall showed that Mieso and Babile, in particular, are taking the highest decreases of -0.76 mm/year and -0.27 mm/year, respectively. Similarly, Chiro and Gurawa are also downward trend by -0.76 mm/year and -1.43 mm/year, (Table 3). The P values, which fall between 0.013 and 0.047, suggest that these shifts are statistically significant across all woredas. In general, Bega rainfall more erratic and it is more changeable than Belg and Kiremt. Because of that, the reliability is weakening, which then reduces the ability for pasture regrowth and soil moisture recharge in the study woredas.

This trend aligns with earlier studies that reported a decline in dry-season rainfall and highlighted its impact on agro-pastoral systems in eastern Ethiopia, where reduced precipitation disrupts both cropping and livestock management arrangements [27]. Similarly, [63] reported Bega season rainfall indicated decreasing rainfall trends in majority of the study station. Similarly, this decreasing of Bega rainfall year after year increase vulnerability in Mieso, Chiro, Gurawa, and Babile, by reducing soil water and pasture supply for their livestock. To respond to these issues, putting in place coping measures like water retention, planting drought-tolerant forage, safeguarding fodder for livestock through the dry spell, and using irrigation for forage crops, becomes crucial in how we handle drought during Bega across Eastern Oromia, Ethiopia.

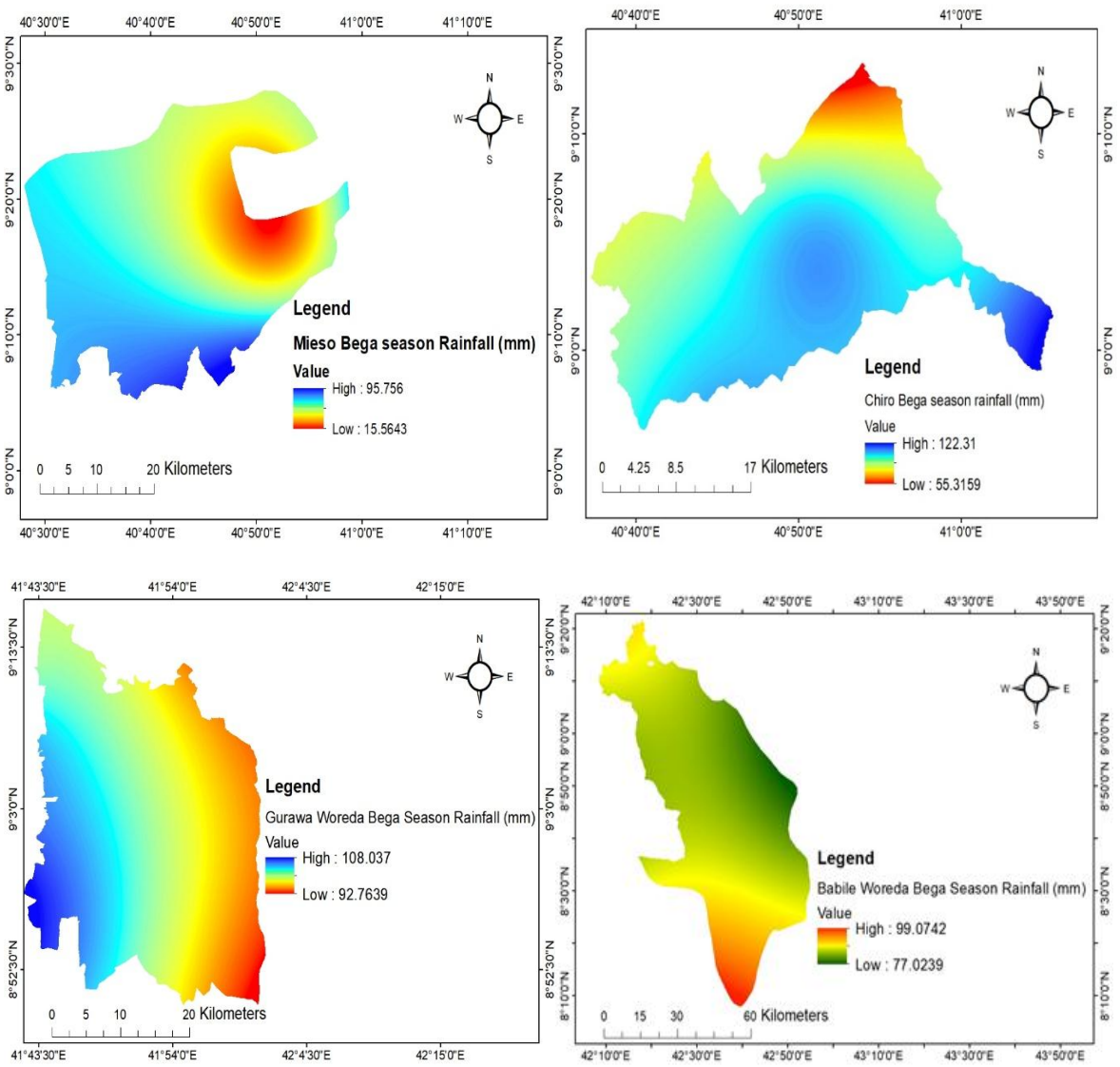


Figure 6 (a–d). Spatial distribution of Bega (October–January) rainfall across Mieso, Chiro, Gurawa, and Babile districts during 1992–2024. Rainfall variability is evident: Mieso ranged from 15.5 to 95.5 mm (mean =55.5 mm); Chiro 55.3 to 123.3 mm (mean=89.3 mm); Gurawa 92.7 to 108.04 mm (mean 100.4 mm); and Babile 77.02 to 99.02 mm (mean 88.0 mm). Blue shading indicates maximum rainfall, whereas red shading highlights minimum rainfall distribution in the study areas. The heterogeneous distribution across and within stations underscores localized climatic differences, with Chiro exhibiting the widest range and Gurawa showing the most stable pattern.

Table 3: Seasonal and Annual rainfall characteristics in Mieso, Chiro, Gurawa, and Babile Woredas, Eastern Oromia (1992–2024)

Variable	Tests	Woredas (Stations)			
		Mieso	Chiro	Gurawa	Babile
Belg rainfall (mm)	Minimum	35.3	258.9	97.9	68.2
	Maximum	308.4	628.7	681.5	343.9
	mean	177.7	299.4	295.4	191.5
	CV(%)	26.8	33.5	40.9	35.3
	SD	68.2	100.3	121.06	67.5
	P-value	0.062	0.096	0.26	0.15
	β	-0.95	-1.35	-0.56	0.011
	Zs	1.087	0.12	0.237	0.21
Kiremt rainfall (mm)	Minimum	197.5	225.2	149	47.7
	Maximum	433.7	712.8	693.7	181.8
	Mean	317.5	447.4	340.5	93.7
	CV (%)	20.6	27.7	36.4	37.06
	SD	65.5	132.2	124.1	34.7
	P-value	0.098	0.061	0.28	0.057
	β	-0.015	1.65	3.75	-0.24
	Zs	-2.3	0.06	0.47	-0.23
Bega rainfall (mm)	Minimum	13.1	31.7	28.8	20.1
	Maximum	125.5	258.9	228.7	220.5
	Mean	68.6	109.18	97.2	98.2
	CV(%)	66.8	47.6	44.4	51.7
	SD	45.8	52.03	43.19	50.8
	P-value	0.80	0.58	0.13	0.79
	β	-0.76	-0.78	-1.43	-0.27
	Zs	0.25	0.55	1.5	0.27
Annual rainfall (mm)	Minimum	401.1	559.6	393.7	187
	Maximum	760.2	1152.2	1046	527.7
	Mean	563.8	886.05	733.5	568.6
	CV(%)	34.4	19.4	22.7	33.6
	SD	194.1	172.5	166.5	190.9
	P-value	0.071	0.078	0.51	0.48
	β	-1.70	0.48	9.6	-0.51
	Zs	-1.019	0.577	1.99	-0.357

Note: Zs = Mann-Kendall test; β = Sen's slope; SD = standard deviation; CV = coefficient of variation; * = indicates significance at $p < 0.05$

Table 3 caption: The table presents descriptive statistics of Belg, Kiremt, Bega, and annual rainfall (mm) for Mieso, Chiro, Gurawa, and Babile woredas in Eastern Oromia during 1992–2024. Variables include minimum, maximum, mean, standard deviation (SD), coefficient of variation (CV%), p-values, linear trend (β, mm/year), and standardized test statistics (Zs). Results highlight spatial and seasonal variability, with Belg and Bega seasons showing higher variability (CV%) compared to Kiremt and annual rainfall. Trend slopes (β) and p-values indicate differing rainfall tendencies across woredas, reflecting localized climatic patterns relevant for agricultural planning.

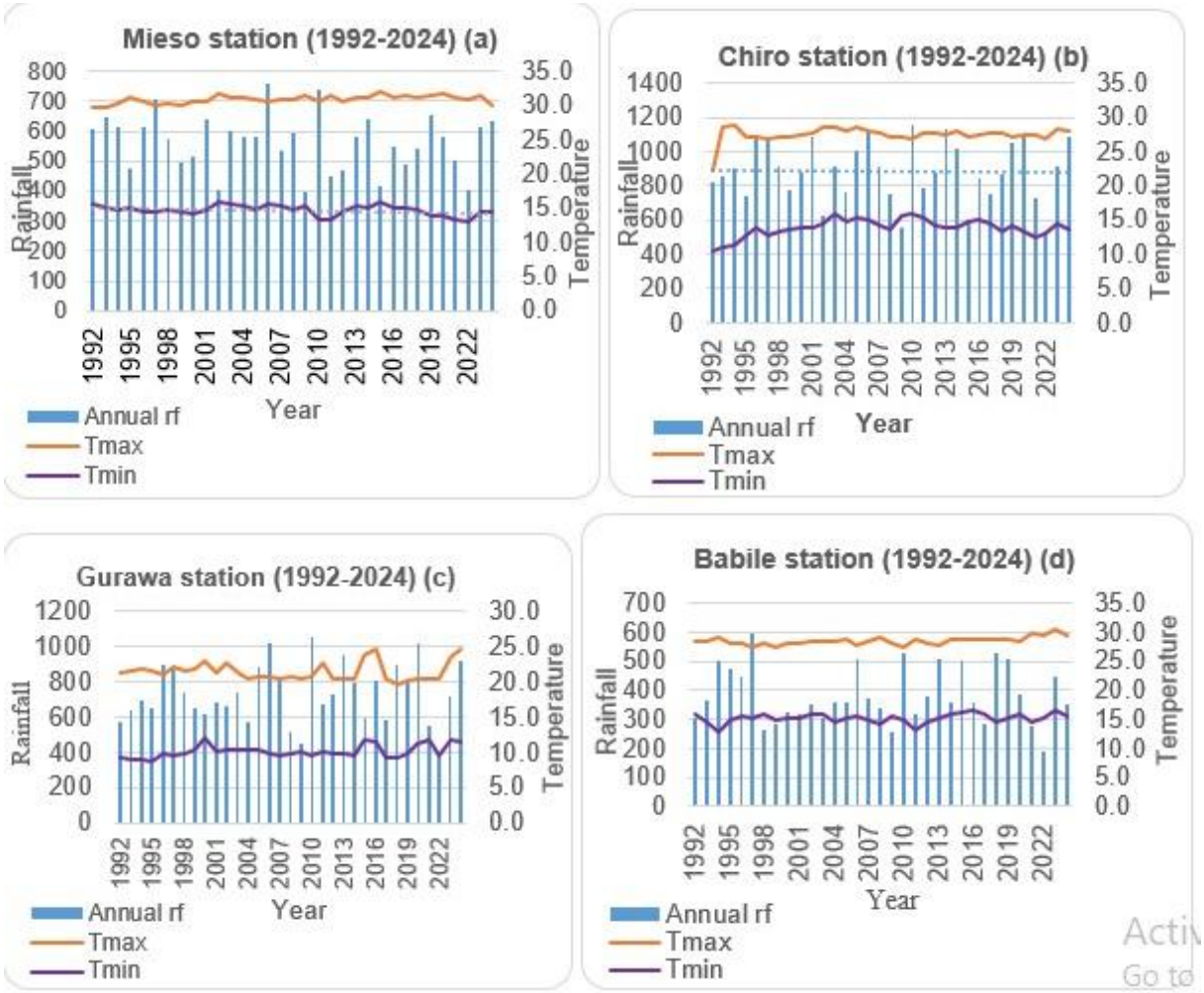


Figure 7 (a-d) yearly rainfall and temperature distribution in Mieso, Chiro, Gurawa, and Babile stations, respectively (1992–2024). Blue bars represent annual rainfall (mm), while red and purple lines show annual maximum and minimum temperatures (°C). The results showed that yearly variability of rainfall were inconsistent or irregular rainfall was observed while both minimum and maximum temperature was significantly increasing across the years. Annual rainfall peaks in July and August during the Kiremt season, while minimum temperatures peak during April and May which is critical for crop growth in the Eastern Oromia, Ethiopia. Belg rains (February–May) are limited and erratic, making them unreliable for early planting.

3.5. Rainfall Variability in the study areas

3.5.1. Analysis of Annual Precipitation Concentration Index (PCI)

Precipitation Concentration Index (PCI) values in Mieso (PCI = 18.1), Chiro (PCI = 17.9), Gurawa (PCI = 18.7), and Babile (PCI = 19.8) (Table 4), The PCI values in all study woredas categorized under moderate rainfall concentration throughout the year, it reflects moderate uneven rainfall distribution across the year and it is not balanced,

but somewhat spread-out. This resulted in smallholder's farmers face seasonal water stress, particularly outside the rainy months. Similarly, [64] stated that the Precipitation Concentration Index (PCI) for annual rainfall shows a moderately irregular distribution, but the seasonal rainfall seems far more irregular. Overall, these results give a strong, climate relevant picture of woreda level rainfall concentration during particular seasons, with changes in onset and in the way rainfall is distributed. Those shifts complicate sensible crop calendar handling and they also increase the likelihood of planning failure and low productivity in the study areas. This finding is significant climate information for district specific rainfall concentration index in the study areas [65].

When PCI values come in below 10, it usually means rain is spread fairly evenly across the year, so irrigation needs drop, and farmers get more freedom for flexible planting and harvesting dates. If PCI is somewhere between 10 and 20, that suggests a middling concentration, where precipitation piles up in a few particular months, and you end up with obvious wet versus dry seasons. Once PCI goes above 20, rainfall becomes strongly focused within a short time period, which then raises the likelihood of flooding and also soil erosion problems. Some strategies crucial in areas with high PCI values in certain season soil and water conservation, to reduce soil erosion and risk of the floods. The results consistent with [66] suggested important of analyzing precipitation concentration variability at different scale to address flood and drought events, to ensure water management and effective crop improvement production.

Similarly, in Northern Ethiopia, some approaches have been put in place to manage the precipitation variability, as discussed by [67] in the Amhara and Tigray regions, households, and communities have sort of adopted different water storage approaches, like tanks, surface underground reservoirs, and rain water harvesting systems. Alongside that, soil and water conservation activities such as terraces and infiltration pit, so that soil erosion is reduced and moisture stay longer [68]. These kinds of strategies seem especially crucial in the study areas showing high variability of precipitation values, because rainfall tends to be more concentrated in certain seasons. When it's like that, the efficient water storage designs, including rainwater collection, take on a key role for strengthening water availability not only for farming but also for livestock.

3.5.2. Analysis of seasonal Precipitation Concentration Index (PCI)

Kiremt (Main rainy season) (June to September)

During Kiremt, Ethiopia's main rainy season, PCI values were from 31.6 in Babile to 37.4 in Chiro, showing irregular up to strongly irregular rainfall concentration (Table 4). This suggests that rainfall is concentrated in a few month result in flooding and soil erosion. Because of the rainy pattern is clustered in a few months there is a strong dependency on those months, and that matters a lot for drought risk in semi-arid areas like Mieso and Babile.

At the same time, area like Gurawa and Chiro highlands, susceptible to the erosion and flooding risks. Following that, [69] reported that in the eastern and western Hararghe zones the seasonal PCI for Kiremt and Belg fell roughly between 29 and 48, which suggests clear intra-seasonal variability. This results aligns with [70], study on South eastern Amhara Zone reported that rainfall distribution is uneven across the season, with (PCI) showing higher irregularity during Belg compared to Kiremt and Annual totals. This indicates that rainfall during Belg is unevenly distributed across the season, concentrated into short periods rather than spread evenly across months. Such irregularity reflects unstable moisture availability, which increases the risk of dry spells, reduces planting reliability, and heightens vulnerability to crop failure.

Kiremt rainfall concentration variability was in the range 22.9% in Gurawa up to 31.7% in Babile, (see Table 4), Gurawa shows a more moderate variability, while Babile and Mieso are more, a greater in variability. Farmers in Gurawa and Chiro can rely on relatively stable rainfall, whereas in Babile and Mieso face higher risks, meaning it makes sense to use adaptation options, such as better water management, shifting crop choices or doing crop diversification, and using drought-tolerant varieties. In line with this results, [71] also reported CV values ranging from 18.14% to 158.8%, and they noted that highland regions had lower CVs, which suggests that reduced variability helps maintain stable rainfall regimes.

Belg season (February to May)

Belg (spring) rainfall PCI values, ranged from 35.9 in Mieso to 39.8 in Gurawa (Table 4), it categorized under highest degree of irregularity, with most of the rainfall being mostly clustered between February and May. When you compare both seasons, Belg PCI rainfall is more irregular in terms of amount and timing, so it lowers the reliability

for crop production, complicate farming decision in the study areas. This results confirmed with [69] in the east and west Hararghe area, Belg season PCI > 30%, reflects highly irregular rainfall concentration. Rainfall concentrated in certain months' results flooding and dry, therefore, the vulnerability of soil to erosion, altering land use strategies.

Similarly, the variability of Belg rainfall concentration values above 30% across all woredas also confirm Belg's season Precipitation Concentration Index (PCI) has an erratic nature. High CV values indicates rainfall is unpredictable, increasing the risk of crop failure in the study areas. Therefore, it necessary to adaptive measures such as short-cycle or drought-tolerant crops, supplemental irrigation, and flexible planting dates in the study areas particularly Mieso and Babile woredas. Consistent with this result, [56], found that rainfall variability in Ethiopia's central highlands is much higher during the Belg season (CV ≈ 30–50%) compared to the Kiremt season (CV ≈ 15–25%)**.** This means Belg rains are far more erratic and unreliable, while Kiremt rainfall is relatively stable and dependable for agriculture. Align with this result [11], reported Belg season rainfall showed high variability**,** with coefficient of variation (CV) values often exceeding 30–40%**,** indicating erratic and unreliable rainfall distribution.

Slopes moved from (-1.6 mm/year) in Mieso up to (1.2 mm/year) in Gurawa, with Mieso, Babile showing a small decline which may worse dry spell risk, while Chiro (0.9 mm/year) and Gurawa (1.2 mm/year) slight increase, resulted in clustering of rainfall, potentially raising erosion risks during intense showers (Table 4). However, the trends are not statistically significant at ($p<0.05$), indicates rainfall variability is inconsistent and driven more by short-term fluctuations than by clear long-term trends in the study areas. This increase or decrease rainfall concentration suggests the need for crop planning adjustment, like crop specific-measures, crop diversification, water management, soil and water conservation to avoid the risk of rainfall concentration in certain months. Similarly, [56], reported that Belg rainfall to have higher variability (CV 30–50%) compared to Kiremt, with slopes showing mixed signals but often not statistically significant.

Align with above results, [70], his research on Watershed-Based Rainfall variability and trends of extreme rainfall events in South East Awash Basin, Ethiopia, reported Belg rainfall slopes showed irregularity, with PCI values >20, confirming uneven distribution and weak long-term trends.

Table 4. Precipitation Concentration Index (PCI), variability, and trends in Mieso, Chiro, Gurawa, and Babile Woredas (1992–2024)

		Woredas (Stations)			
Period	Test	Mieso	Chiro	Gurawa	Babile
Annual	PCI	18.1	17.9	18.7	19.8
	SD	137.5	176.9	190.4	220.6
	CV (%)	32.4	19	29.5	34.5
	P-value	0.26	0.31	0.32	0.27
	Slope (mm/year.)	-4.2	2.6	3.1	2.9
Kiremt	PCI	32.3	37.4	36.8	31.6
	SD (mm)	73.9	92.1	73.9	115.7
	CV (%)	31.5	21.4	26.6	36.9
	P-value	0.23	0.42	0.36	0.45
	Slope (mm/year)	-2.9	0.04	0.9	-2.8
Belg	PCI	35.9	37.6	39.8	36.6
	SD	45.6	47.9	102.6	82.4
	CV (%)	30.5	30.1	33.6	33.6
	P-value	0.21	0.47	0.42	0.06
	Slope (mm/year)	-1.6	0.9	1.2	-2.0

Note: Zs = Mann–Kendall test; RAI = Rainfall Anomaly Index; PCI = Precipitation Concentration Index; * = indicates significance at $P < 0.05$.

Table Caption 4: summarizes annual, Kiremt, and Belg season precipitation concentration index (PCI) values, standard deviation (SD), coefficient of variation (CV%), linear trend slopes (mm/year), and p-values for Mieso, Chiro, Gurawa, and Babile woredas in Eastern Oromia during 1992–2024. PCI values indicate rainfall distribution uniformity, with higher values reflecting greater concentration. SD and CV% measure variability, while slope values show rainfall trends and p-values indicate statistical significance. Results highlight seasonal differences, with Belg season showing higher PCI values (greater rainfall concentration) compared to Kiremt and annual periods.

3.6. Rainfall Anomaly Index (RAI)

Annual rainfall anomaly analysis for Eastern Oromia shows clear spatial and seasonal variations. For example, Gurawa (RAI = 0.93) and Chiro (RAI = 0.18) had somewhat wet conditions, while Mieso (RAI = -0.22) and Babile (RAI = -0.21) (Table 5) indicates slightly dry over study period. Wet anomalies in Gurawa and Chiro suggest relatively favorable for crop, while slight dry in Mieso and Babile indicates moisture stress, increasing vulnerability to recurrent drought and decreasing dependability of Belg season rainfall. The Rainfall Anomaly results confirms that rainfall distribution is irregular across space and season, supporting the need for location-specific adaptation strategies.

The trend of RAI at Gurawa's slope (β = 3.1mm/year), indicates rising rainfall, while Mieso (β = -0.12 mm/year) and Babile (β = -2.9 mm/year) (Table 5) indicating declining

rainfall. But, all those slopes were statistically insignificant, ($p > 0.05$). This magnitude indicates spatial variability of rainfall in the study areas. Similar findings were also described by [71], reported research conducted in Birr Watershed, Upper Blue Nile Basin, the magnitude of annual rainfall was declined by between –1 to –3 mm/year) and not significant at $p < 0.05$, reflecting weak but consistent downward tendencies.

The results in Figure (8a-d), shows yearly Rainfall Anomaly Index (RAI) for Mieso, Chiro, Gurawa and Babile between 1992 and 2024 shows some marked ups and downs, and it really reflects vulnerability toward climate extremes. For Mieso the results of yearly RAI showed as: wet anomalies in 1996, 1997, 1999, 2004, 2018, and 2024, while severe droughts showed up in 2008, 2011, 2015–16, 2017, 2021, and 2023. Moderate dryness appeared in 2002, with a bit of slight dryness in 2000 and 2013. Years close to normal were also quite frequent, including 1992–95, 2001, 2003, 2005–06, 2009–2010, 2012, 2014, 2019, and 2022 (Figure 8a).

This pattern indicates that rainfall in Mieso woreda has been highly erratic, alternating between extremes of wet and dry conditions, which complicates agricultural planning and heightens vulnerability to climate shocks. The El Niño-Southern Oscillation (ENSO) phases powerfully influence yearly rainfall unpredictability, with El Niño events typically related with dry conditions and La Niña phases linked to wetter conditions. The pronounced increase or decrease variability highlights the area's sensitive exposure to climate extremes.

In the same way, Chiro's yearly Rainfall Anomaly Index (RAI) also showed strong back-and-forth variability, which indicates the area's heightened exposure to climate extremes. Wet anomalies came up in 1996, 2004, 2005, 2007, 2009, 2012, 2018, 2020, 2022, and 2024, but severe droughts were recorded in 2001, 2011, 2014, 2015–16, and 2023 (Figure 8b). Then there were moderate dry periods in 1993, 2002, 2003, 2017, 2019, and 2021, while near normal years showed up in 1992, 1994–95, 1997–2000, 2006, 2008, 2010, and 2013. The RAI record demonstrates that rainfall in the Chiro woreda is marked by strong inter-annual variability, sporadic between wet anomalies and droughts, with irregular normal years. This unpredictable pattern complicates agricultural planning and underscores the need for adaptive strategies to manage climate risks. The results reflected that, irregular precipitation makes farming plans difficult, meaning adaptive measures are needed like water harvesting, crop diversification, and more resilient farming practices, rather than relying on "usual" seasons.

In Gurawa woreda the yearly Rainfall Anomaly Index (RAI) had a lot of back and forth, during the study periods 1992-2024. There were wet years like 1996, 1999, 2004, 2009, 2012, 2018, 2020, 2022, and 2024 (Figure 8c), which means rainfall was higher than the average by a noticeable margin. On the other hand, strong dry spells showed up in 2002, 2003, 2008, 2011, 2014–17, 2021, and 2023, and near normal situations were noted in 1992–95, 1997–98, 2000–01, 2005–07, 2010, 2013, and 2019 (Figure 8c). The yearly RAI demonstrates that rainfall in the study districts is highly erratic, alternating between wet anomalies, severe droughts, and near-normal years. This variability complicates agricultural planning and underscores the need for adaptive, climate-resilient strategies. Garawa's rainfall indicates strong year-to-year variability, and this kind of unpredictability makes agricultural planning difficult, so adaptive responses matter a lot such as water harvesting, crop diversification, and soil conservation, not just one measure.

For Babile, the rainfall anomaly review across 1992–2024 also showed strong variability. Wet anomalies were seen in 1992, 1996–2001, 2006, 2018, and 2021. Severe droughts were recorded in 2003, 2004, 2012, 2014, and 2015. Moderate droughts came in 2002, 2007, 2008, and 2011, and then slight droughts in 2013, 2016, 2017, and 2023 (Figure 8d). ENSO phases clearly played a role: El Niño years (2002, 2015) matched severe drought, whereas La Niña years (1996, 1999, 2000, 2018, 2021) generally connected to wetter conditions. Overall, rainfall anomalies in Babile underline a kind of jumpy, erratic pattern, so farming decisions get complicated and vulnerability rises in the district.

Kiremt season anomalies actually pointed to rather wet conditions around Gurawa (RAI = 0.29) and Chiro (RAI = 0.26), with positive slopes, while Babile (RAI = –0.27, β = –2.8 mm/year) shown (Table 5) suggests rainfall has been dropping, so drought risks go up. These differences may be due to landscape variations, where the higher elevations tend to hold a steadier rain pattern, and the lower areas look more irregular.

For Belg, the anomalies were basically all negative Mieso = –0.16, Chiro = –0.23, Gurawa = –0.29, Babile = –0.22 (Table 5), and this confirms that Belg can be unreliable when it comes to long cycle crops. Also, the decline in the slopes (β = –1.6 to –2.0 mm/year), indicates a downward tendency, which can expose farmers to planting failures and food insecurity. Studies confirm Belg's erratic nature, underscoring the need for localized adaptation strategies such as short-cycle crops, supplementary irrigation, and soil conservation.

Table 5: Annual, Kiremt, and Belg Rainfall Anomaly Index (RAI), Trends, and Statistical Significance in Mieso, Chiro, Gurawa, and Babile Woredas (1992–2024)

		Woredas (Stations)			
Period	Test	Mieso	Chiro	Gurawa	Babile
Annual	RAI	**-0.22**	**0**.18	0.93	-0.21
	Slope (mm/year)	-0.12	0.90	3.10	-2.90
	P-value	0.19	0.52	0.21	0.81
Kiremt	RAI	-0.319	0.26	0.29	-0.27
	Slope (mm/year)	-2.90	0.04	0.90	-2.80
	P-value	0.13	0.54	0.11	0.13
Belg	RAI	-0.16	-0.23	-0.29	-0.22
	Slope (mm/year)	-1.6	-0.90	-1.20	-2.0
	P-value	0.55	0.72	0.44	0.61

Note: Zs = Mann–Kendall test; RAI = Rainfall Anomaly Index, mm/yr.=millimeter per year, * = denotes significance at P < 0.05.

Table Caption 5: The table presents annual, Kiremt, and Belg rainfall anomaly index (RAI) values, linear trend slopes (mm/year), and associated p-values for Mieso, Chiro, Gurawa, and Babile woredas in Eastern Oromia during 1992–2024. RAI indicates deviations from average rainfall, slope values show the direction and magnitude of rainfall trends, and p-values reflect statistical significance. The results indicate spatial and seasonal variability, with Gurawa showing positive anomalies and increasing trends, while Babile exhibits negative anomalies and declining rainfall patterns.

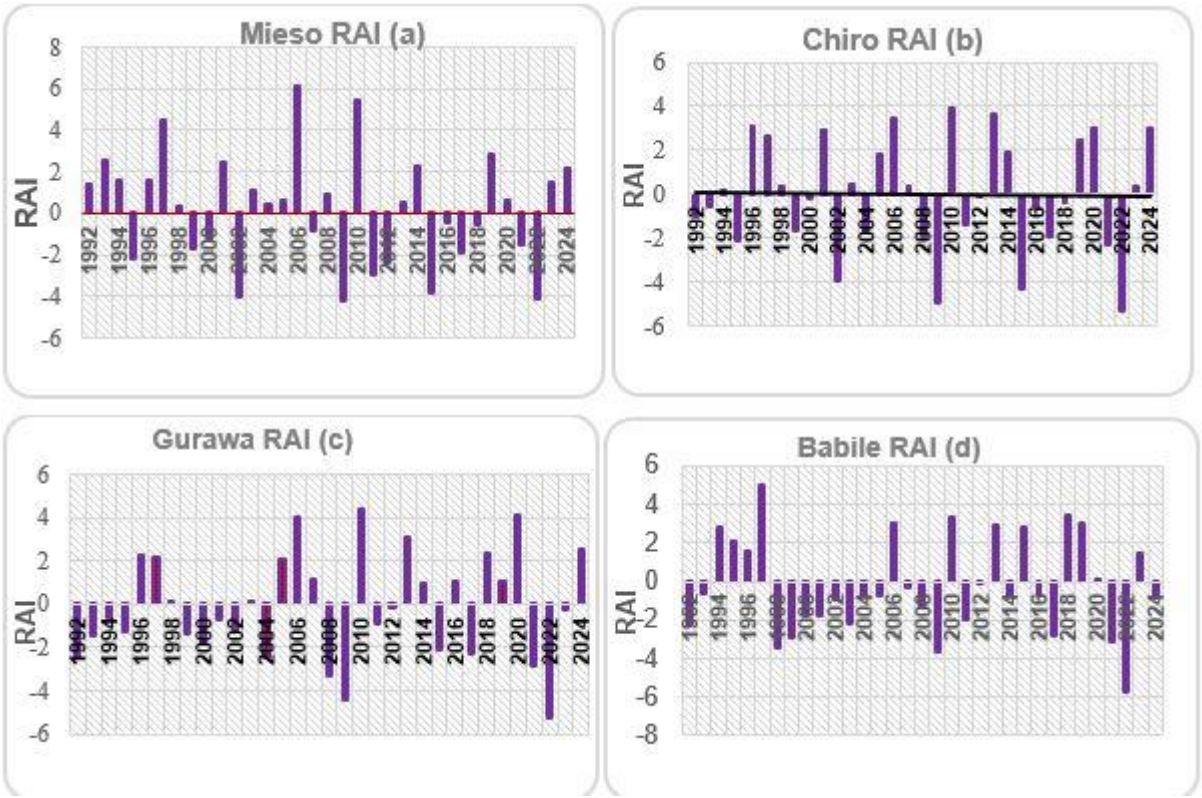


Figure 8 (a–d). Annual Rainfall Anomaly Index (RAI) values for Mieso, Chiro, Gurawa, and Babile Woredas (1992–2024)

Figure caption 8 (a-d). The graphs present annual Rainfall Anomaly Index (RAI) values for Mieso, Chiro, Gurawa, and Babile woredas in Eastern Oromia during 1992–2024. Panels (a–

d) represent each location respectively, showing internal variability with alternating positive and negative anomalies. The plots highlight fluctuations across three decades, reflecting periods of above-average and below-average rainfall conditions, thereby indicating variability in rainfall distribution and its implications for agricultural planning in the study areas.

3.7. Rainfall onset (SOS), Cessation date (EOS), and Length of growing period (LGP)

3.7.1. Belg Season rainfall (February–May)

Eastern Ethiopia experiences a bimodal rainfall pattern, basically Belg (February–May) and Kiremt (June–September). When we look at Belg onset from 1992 up to 2024, there is clearly strong spatial and temporal variability. For example, Mieso and Babile both tend to start late onset date (April 2–3; DOY 94.5 and 93.5), and they also come with large uncertainty, above 30% CV. Chiro on the other hand has the earliest onset (March 15; DOY 74.7) but it still considerable variable with CV = 31.8%. Gurawa (March 29; DOY 89.4) falls in between, this extremes moderate variability (Table 6, Figure a-g).

These variabilities may be due to topographic effects, highland areas grab the moist air sooner, while lower places often wait longer because evapotranspiration is stronger there. When the onset starts late, and the Belg rains are unstable, sorghum and maize yields tend to drop in the study areas where those crops are mainly grown. The main issue is that these unpredictable conditions shorten the growing duration, and they also weaken planting dependability, so the overall result is less time and less reliable moisture for crop establishment. This points to the need for early-maturing crop varieties, plus supplemental irrigation, and better soil and water conservation practices in the study areas. As a consequence, farmers may have to shift planting dates, and they may need to rethink when the rainfall onset actually happens, in order to improve crop performance.

This matches the findings by [72], Belg cessation dates across Eastern Oromia mostly showed up in early to mid-June, but indeed it was not the same everywhere, woredas behaved a little different. Mieso had the stable end date (DOY 155.6, June 3; CV = 4.8%) (Figure 10a), which makes sense because even with that late starting signal, the termination still stayed consistent. Chiro ceased slightly later (DOY 165.6, June 14) and still kept relatively low variability. Gurawa, on the other hand, extended

into mid-June (DOY 169.4, June 17). Babile started earlier (DOY 163.7, June 11), it had moderate variability and a broader spread in the percentiles (Table 6, Figure 10h).

On the whole, Belg cessation was less variable than onset, and it seemed more affected by broad climate forces rather than neighborhood details. For instance, weakening Indian Ocean moisture inflow and the migration of the ITCZ likely played a bigger. This matches with also reports, [73] namely that Belg cessation in Eastern Ethiopia is largely governed by large-scale climate drivers such as reduced Indian Ocean moisture transport, shifts in the Inter-Tropical Convergence Zone (ITCZ), and ENSO phases. Meanwhile, the differences in onset are described as coming more from local causes like topography, elevation, and small micro-climates.

The length of Growing periods (LGP) during Belg season is about 65–81 days, and it was also quite changeable, especially in the lowland districts like Mieso and Babile (Table 6), where the late start of rains and strong evapotranspiration basically squeezed the cropping window. This might happen because high surface temperature in semi-arid areas can shorten the crop's maturity, in turn reducing potential yields. However, Chiro and Gurawa still provided a slightly longer growing periods. Overall, in the study areas, crop varieties that need more than 81 days to mature cannot be established successfully using rainfall alone. On the other hand, maize varieties with a 90-day cycle do not fully benefit from the available growing period, since the short duration leaves close to two months unused. These limitations, practically speaking, restrict the feasibility of longer duration crops, so short cycle or drought tolerant varieties, along with small scale irrigation practices, become essential to maintain production.

3..7.2. Kiremt season (June to September)

The Kiremt (Summer) season is a critical rainfall period for smallholders in the Ethiopia, especially in the eastern regions. Characterizing rainfall variability during this season is essential for sustainable farming systems and supporting livestock production. The results in figure 10 below showed that a strong spatial variability in onset and cessation dates, and length of growing period (LGP). In Mieso, the onset is really erratic (June to August, mean DOY 189.6 July 8, CV 30.4%) (Table 6, Figure 10 b), suggesting that in some seasons the rains could start much sooner (early June) or much later (mid-August) and this makes planting decisions more or less hard for farmers because the timing becomes less dependable. Even so, the cessation is

comparatively stable around mid-October (mean DOY 285.2, October 12) with low variability (CV = 4.5%) (Table 6). This indicates rainfall cessation remains stable each year, even when onset is delayed.

The length of the growing period on average around 97 days, but it really ranging from roughly 50 up to 153 days (Table 6). As a result, the rainfall pattern cannot reliably support long-cycle crops like maize or sorghum, which demand four to five months of continuous moisture. When the rains start late and then stop early, the growing period itself gets shorter, which means there is less time for the crop to finish developing, and that in turn bumps up the chance of yield losses. Basically, it shows the rainfall is ending before the crop can mature or fully complete its life cycle, which also tends to enhance those yield losses. So, farmers might have to change their approach by sowing short cycle varieties, or drought tolerant types that can mature within about two to three months, and these should be supported by irrigation. As a result, growers in the study area may need to shift planting dates, and revisit the timing of rainfall onset, so they can improve crop yields.

Similarly, [74], reported that a delayed onset and earlier cessation of rains in maize based zones of Ethiopia shorten the growing period by 10–71 days, this makes farmer's reconsider crop choices and management practices to sustain crop production under increasing irregular rainfall. This suggest adaptation measures like short cycle varieties that are drought tolerant, and also shifting the planting date so you can improve resilience. In a similar vein, Babile shows more onset variability, with the start of season coming as early June (DOY 153) up to late September (DOY 272) and the mean onset around July 13 (DOY 194) (Table 6). Its end happens roughly about one week later than Mieso, and the variability is lower than Mieso, with (CV=13.4%) (Table 6 Figure 10h).

The LGP for Mieso is the shortest on average, about 85 days, compared to Mieso, Chiro, and Gurawa woredas. It also varies a lot (CV = 35.9%) (Table 6). This kind of evenness in LGP really limits the possibility of long cycle crops, so farmers use short-cycle crops or drought tolerant varieties to overcome the variability of growing period. The length of the growing period, or LGP, needs careful attention, because knowing the risk of yield loss linked with cultivars of different maturity groups each one having its own water demands at separate growth stages. With that kind of understanding, it becomes easier to select the most suitable cultivar for sowing, especially when the onset date can shift. In arid and semi-arid areas, the growing period tends to match

short season crop maturity, while longer season cultivars often cannot finish their water needs, mainly because moisture stress kicks in. In agreement with these findings, [75] stated that weather guided farming practice can combine genetic options with management approaches, which then gives farmers some usable alternatives to lessen drought effects.

Chiro and Gurawa districts, during the Kiremt season, offer more favorable cropping conditions, compared to Mieso and Babile. In Chiro, the onset happens roughly July 29 (mean DOY 183.2, CV = 18.3%), and the cessation stays fairly steady in mid-October (mean DOY 286.5, CV = 4.5%) (Table 6, Figure 10d). The growing period averages 103 days (range 83–153, CV = 25.4%), meaning it is moderately variability. For Gurawa, the earliest onset was noted on June 24 (mean DOY 175, CV = 26.1%), and cessation is again stable (mean DOY 285.7, CV = 4.7%). Gurawa also shows the longest cropping window among the districts, averaging 110 days (range 63–151, CV = 19.1%) (Table 6, Figure 10d). So, the earlier onset in Gurawa, probably indicates that longer maturity type crop cultivars could perform better when the onset date happens late. The way onset differences play out across Eastern Oromia is basically influenced by the uneven landforms, altitude and what the local weather does, including circulation effects, not just that but also by big scale drivers like ENSO and shifts in the ITCZ [76].

Table 6: Seasonal rainfall characteristics in selected Woredas of Eastern Oromia (1992–2024)

Woreda (stations)	Season	Variable	Min.	Max.	Mean	Std	CV (%)	Q1 25%.	Q2 50%	Q3 75%
Mieso	Belg	SOS (DOY)	41	217	94.5	33.9	35.8	78	87	106
		EOS (DOY)	152	186	155.6	5.2	4.8	152	152	157
		LGP	55	115	65	22.7	34.9	52	67	115
	Kiremt	SOS (DOY)	153	224	189.6	57.5	30.4	179	190	201
		EOS (DOY)	274	315	285.2	13.0	4.5	274	278	294
		LGP	50	153	97	24.7	25.5	79	95	159
Chiro	Belg	SOS(DOY)	38	105	74.7	23.8	31.8	62	78	90
		EOS(DOY)	152	172	165.6	5.3	3.4	152	152	157
		LGP	52	123	85	26.3	33.9	67	79	95
	Kiremt	SOS (DOY)	153	205	183.2	33.5	18.3	177	183	194
		EOS (DOY)	274	315	286.5	12.9	4.5	274	285	294
		LGP	83	153	103	26.2	25.4	91	99	111
Gurawa	Belg	SOS (DOY)	53	125	89.4	29.4	32.8	78	87	104
		EOS (DOY)	152	208	169.4	12.9	7.9	152	164	170
		LGP	39	113	74.9	19.7	25.8	60	70	92
	Kiremt	SOS (DOY)	153	211	175.4	45.8	26.1	153	177	211
		EOS (DOY)	274	320	285.7	13.4	4.7	274	276	293
		LGP	63	151	110.1	21.1	19.1	96	111	125
Babile	Belg	SOS (DOY)	68	121	93.5	33.1	35.4	86	92	102
		EOS (DOY)	152	191	163.7	13.1	8.0	152	158	175
		LGP	31	102	65	24.9	38.4	59	66	79
	Kiremt	SOS (DOY)	153	272	194	25.9	13.4	178	192	207
		EOS (DOY)	274	307	279.7	9.8	3.5	274	274	281
		LGP	27	122	85.2	29.9	35.9	70	89	96

Where min. minimum, max. maximum, SOS (DOY)=start of rainy day, EOS (DOY)= cessation date, DOY, days of the years, LGP (Days), Length of Growing Periods)., Q1(25%). = lower quartile, Q2 (50%) median, Q3 (75%) upper quartile range

Table 6, summarizes seasonal rainfall characteristics for Mieso, Chiro, Gurawa, and Babile woredas in Eastern Oromia during 1992–2024. Variables include start of season (SOS, day of year), end of season (EOS, day of year), and length of growing period (LGP, days) for Belg and Kiremt seasons. Descriptive statistics presented are minimum, maximum, mean, standard deviation (Std), coefficient of variation (CV%), and quartiles (Q1, Q2, Q3). These values highlight variability in rainfall onset, cessation, and growing period across the study sites, providing understandings for agricultural planning.

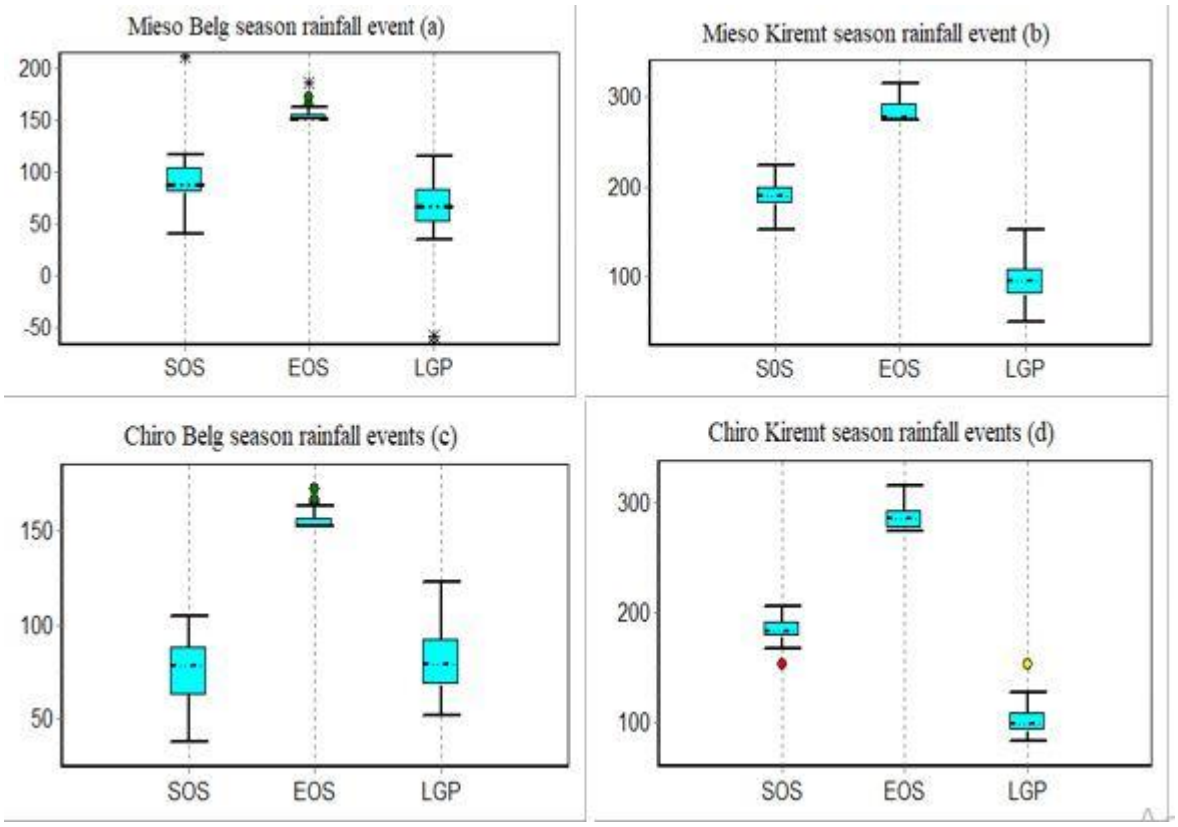


Figure 10 (a-d): Seasonal Rainfall Characteristics in Mieso and Chiro Woredas, Eastern Oromia, Ethiopia (1992–2024)

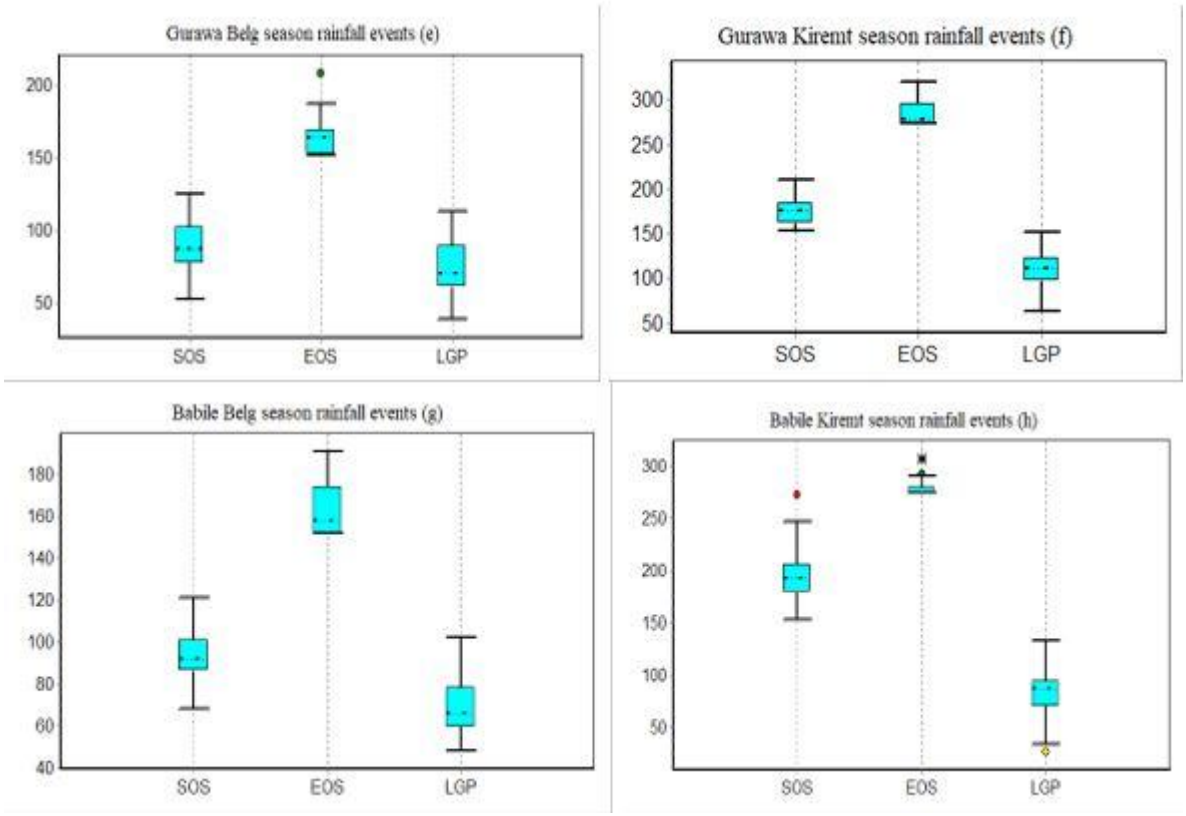


Figure 10 (e–g). Seasonal Rainfall Characteristics in Gurawa, and Babile Woredas, Eastern Oromia, Ethiopia (1992–2024)

Figure 10 (a-g). The box plots illustrate seasonal rainfall characteristics across Mieso, Chiro, Gurawa, and Babile woredas in Eastern Oromia during 1992–2024. Each panel (a–g) shows the distribution of start of season (SOS), end of season (EOS), and length of growing period (LGP). Turquoise boxes represent the interquartile range (IQR), the line inside indicates the median, and whiskers mark the extremes. The plots highlight variability in onset (days 130–150), cessation (days 270–290), and growing period (150–200 days), providing understandings useful for agricultural planning.

3.8. Probability of dry spell occurrence in the study areas

The probability analysis of dry spell occurrence reveals clear spatial and seasonal differences across districts. By early April (DOY 95), short dry spells lasting five days were almost high in Mieso and Babile (85-95%) (Figure 11a, Figure 11d). Probabilities for 7-day spells also remained high (55-65%), and longer dry spells of 10–15 days showed similarly increased risks.

Chiro presented a contrasting pattern, with lower probabilities, particularly for longer spells (sp10=55%, sp15=35%) (Figure 11b). This relative reduction in dry spell risk corresponds with more favorable crop production conditions. Gurawa occupied an intermediate, with probabilities around sp5 = 85%, sp7 = 85%, sp10=75%, and sp15=55%. These findings align with [77], who reported that the likelihood of agricultural dry spells exceeding 10 days in East Africa ranges from 20% to over 70%, depending on rainfall onset. Similar observations were reported by [78], the result of rainfall variability in the Daro Lebu woreda, west Hararghe Zone, Oromia showed that the probability of a 5-day dry spell reached 99% and a 7-day spell about 80%.

By the peak of the rainy season (around DOY 200), probabilities declined sharply across all districts, with reductions of 25–90% compared to early April. In Mieso, sp5 dropped to 30% and sp10 to 5%. In Chiro, sp5 fell to 10%, while sp15 became negligible. Gurawa maintained intermediate values (sp5 = 25%, sp7 = 15%) (Figure 11c). Babile remained more exposed, with sp5 still around 40% and occasional sp15 events after mid-September (Figure 11d).

Overall, the results show that dry spell probabilities (sp5, sp7, sp10, sp15) vary significantly across woredas, with impacts differing by location. Dry spell pressure was consistently higher in Babile and Mieso, even during the Kiremt season (June–

September), while Chiro was least affected. These patterns suggest that Mieso and Babile are the most drought-prone districts, underscoring the importance of integrating dry spell probability analysis into crop planning. In lowland areas, reliance on short-cycle or drought-tolerant varieties, supplemented by irrigation and soil moisture conservation, is critical to stabilizing yields.

In Haramaya district, the probability of a 5-day dry spell was 80% near DOY 181, decreasing to below 50% by DOY 221. Taken together, these findings reinforce that intra-seasonal rainfall variability rather than annual totals constitutes the primary source of agricultural risk in semi-arid Eastern Oromia, consistent with regional studies. [79], reported that during the Belg season, the probability of a 5-day dry spell is extremely high (≈90%), while 7-day dry spells occur with about 75% likelihood, exposing farmers to severe moisture stress and making the season unreliable for long-cycle crops. In June, at the onset of Kiremt, dry spell probabilities decline but remain notable: 5-day dry spells occur in roughly 65% of cases, disrupting planting and early growth, while less frequent 10–15-day dry spells can still cause serious damage during crop establishment.

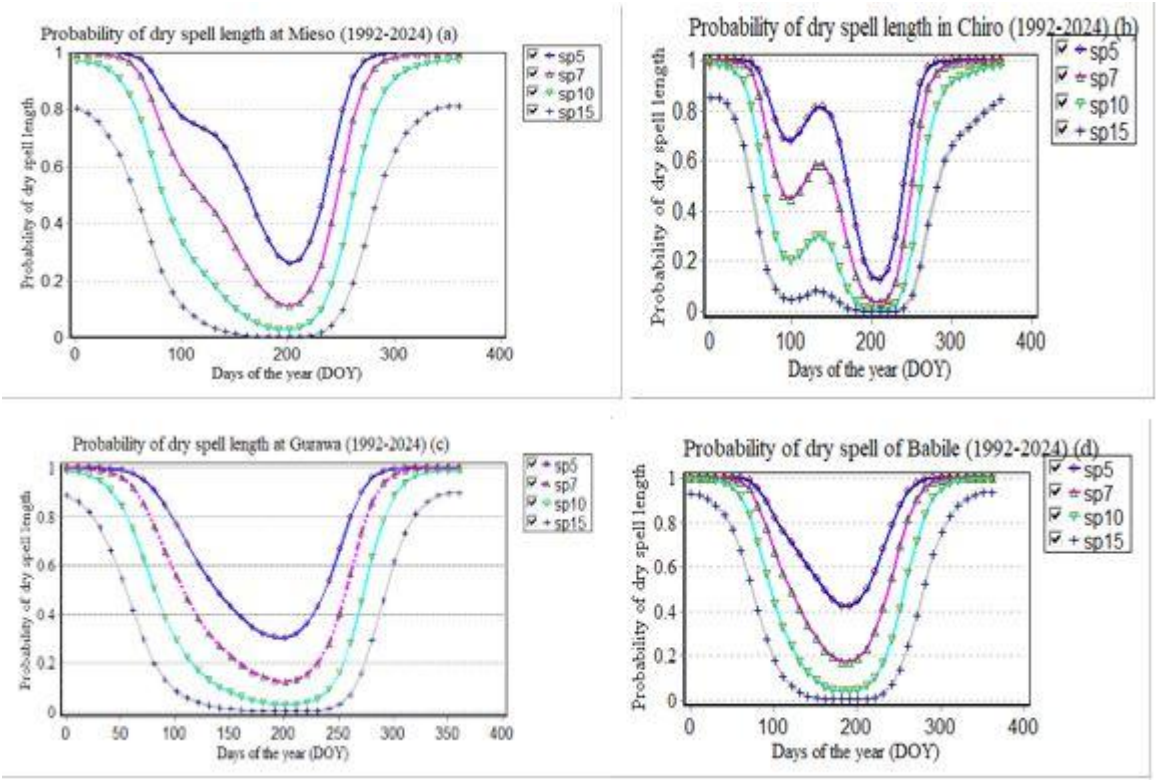


Figure 11 (a-d). Probability of dry spells lengths in Mieso, Chiro, Gurawa, and Babile (1992–2024)

Figure 11(a-d). The figures show the probability of dry spells of varying lengths (5, 7, 10, and 15 days) across Mieso, Chiro, and Gurawa during 1992–2024. Panels (a–d) represent each location respectively, the curves show seasonal variation with higher probabilities at the beginning and end of the year and lower probabilities around midyear (2001 Days of the Year).

3.9. Limitations

The present study is subject to several limitations that really should be acknowledged. First, the rainfall analysis depended on data from a limited number of meteorological stations, which brings in a spatial bias and it can be that micro-climatic variations in unmonitored zones were simply missed.

This kind of dependence on station records also suggests that non indexed or less accessible local datasets, like farmer reports or community observations, were not used. so the diversity of perspectives might be somewhat narrowed. Second, there was a linguistic and methodological tilt toward quantitative indices, and because of that qualitative insights, such as indigenous knowledge systems, may have been understated. those insights could have helped with the context, and not only the numbers. Third, although indices like the Coefficient of Variation and Precipitation Concentration Index were used, these usual metrics do not fully capture the on the ground consequences of rainfall variability for farming, for instance crop failure risks or how resilient households are under stress. Fourth, the temporal span of 32 years, even if it is fairly substantial, might still fail to catch longer climate cycles or rare extreme events, therefore the completeness of the analysis could be restricted. Finally, the tools and methods applied were mostly statistical and interpolation based, which creates technical constraints because they do not bring in advanced climate models, GIS based simulations, or socio economic indicators that could support a wider angle assessment of rainfall variability and its agricultural outcomes.

Future work can address these limitations by bringing in more diverse datasets, including non-indexed local records along with indigenous knowledge, while also increasing spatial coverage through remote sensing and GIS tools. In addition, applying advanced climate modeling approaches would strengthen the interpretation. It would also help to integrate both quantitative and qualitative metrics, so the evaluation becomes more connected to actual local relevance of rainfall variability, and

in turn this could improve the reliability of agricultural planning strategies in Eastern Oromia.

4. CONCLUSIONS

"In this study, we found that rainfall variability in Eastern Oromia is driven more by intra-seasonal fluctuations than by annual totals." Alterations in the timing of rainfall start and ends, changing probabilities of dry spells, and uneven rainfall distribution all directly heighten agricultural risk." Districts such as Mieso and Babile often face unreliable rainfall onset, shorter growing seasons, and recurrent dry spells, emphasizing localized agricultural challenges. Meanwhile, districts such as Gurawa and Chiro enjoy extended and relatively stable growing windows.

The RAI reflects marked year-to-year variations, while the Precipitation Concentration Index (PCI) reveals that rainfall is irregularly distributed across time mainly in the lowlands, where intense bursts are often followed by prolonged dry spells. All together spatial pattern points to a clear climatic gradient in the study areas. Overall, the spatial pattern reveals a climatic gradient: the highlands Woreda like Gurawa and Chiro benefit from orographic uplift that enhances rainfall, whereas the lowlands continue to suffer from persistent moisture shortage. The findings indicate that adaptive measures ranging from crop diversification and soil conservation to agroforestry and small-scale irrigation are critical, provided they align with local risk context particularly Mieso and Babile Woreda. For rain-fed agriculture to sustain and food systems to remain secure in lowland, Eastern Oromia, adaptive measures must be reinforced through better early warning and climate-smart planning.

Data availability statement

Data available on request from the author.

Code availability

Not applicable

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Authors contributions

For this work, the authors contributions are listed like: Y.A-A., A.M-H. took part in conceptualization and design the study. B.T-O., F.M-L. handled software, plus data analysis and all that. Then A.A-A. was involved with supervision and contributed to the

first draft writing, in a general sense. After that, all the authors reviewed the whole thing and approved the final version, so yeah it's settled.

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