Regional Environmental Change (2026) 26:104
https://doi.org/10.1007/s10113-026-02591-1

RESEARCH

A comparison of observed and perceived seasonal climate regimes in a rural socio-ecological system in the northeastern South Africa

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Received: 15 January 2026 / Accepted: 13 April 2026 / Published online: 8 May 2026
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Abstract

This study investigated perceptions of climate change among residents of 12 villages in Bushbuckridge, Mpumalanga, South Africa, through household surveys and focus group discussions. These perceptions were compared with climatic trends derived from Skukuza meteorological station data (1981–2023), focusing on summer seasonal temperature and rainfall patterns. The analysis of meteorological station data revealed significant increases in seasonal maximum temperatures, a marked decline in the number of wet days, and high interannual variability in total seasonal rainfall. While local perceptions aligned with recorded trends of rising temperatures, delayed onset of the rainy season, and more erratic rainfall patterns, discrepancies emerged regarding total rainfall amounts; participants perceived an overall decline, whereas meteorological data showed no statistically significant long-term trend in seasonal rainfall totals. These findings highlight the value of integrating local knowledge into climate change research. Local perceptions provide critical insights into micro-level climate impacts, such as changes in rainfall frequency and intensity, that may not be evident in observational data. Combining these perspectives with scientific measurements can enhance the design of culturally relevant and effective climate adaptation strategies. This approach fosters stronger community engagement and ensures that policies address both the observed and perceived impacts of climate change, thereby supporting more sustainable and inclusive responses at local and national scales.

Keywords Climate change · Rural socio-ecological system · Observed and perceived seasonal climate regimes

Introduction

Climate change is widely recognized as one of the most significant challenges facing humanity (IPCC 2023). Observed and modeled climate data have been essential in determining the extent to which people are genuinely at risk from ongoing climate change. A growing body of research predicts and analyzes climate impacts (Navarro-Racines et al. 2020; Schwarzwald et al. 2022), yet gaps remain in understanding how people perceive these risks in their daily experiences. Such perceptions are crucial (Rühlemann and Jordan 2021), as they shape responses, preparedness, and decision-making

Communicated by Kerrie Pickering

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amid changing weather patterns (Carman and Zint 2020; Orlove et al. 2020; Siders and Pierce 2021).

The IPCC reports widespread temperature increases across Africa (Ranasinghe et al. 2021), with annual heatwave frequency now exceeding natural climate variability (Engdaw et al. 2022). Rainfall trends, however, remain inconsistent: only about 20% of Africa shows significant changes in annual maximum daily precipitation, concentrated mainly in central Africa (mostly negative). The reliability of these trends remains limited due to the sparse distribution of rain gauges. Excluding central Africa, 37% of trends are positive (e.g., Sahel, Kenya, Tanzania, Gulf of Guinea) and 63% are negative (e.g., South Africa, Namibia, inland West Africa) (Marra et al. 2022), with some datasets showing conflicting directions of change (Cattani et al. 2018; Contractor et al. 2020). These inconsistencies reflect high variability, differing datasets and methods, and sparse, low-quality station data (Contractor et al. 2020; Harrison et al. 2019), limiting reliable climate trend analysis and adaptation planning. Additionally, instrumental measurements often fail to capture the nuanced ways in which communities perceive and experience environmental changes, underscoring the need for integrating diverse knowledge systems into climate assessments and adaptation strategies (Haag et al. 2021; Reyes-García et al. 2024).

Given the uncertainties and limitations surrounding observed climate trends (Gudmundsson et al. 2021), integrating meteorological data with local knowledge can provide a more complete picture of climatic changes (Serrao et al. 2025). Studies that integrate local perceptions with meteorological data are growing worldwide (Balasha et al. 2023; Nyang'au et al. 2021), as researchers aim to understand how climate change and its trends are experienced and interpreted across different contexts (Ricart et al. 2022). As a result, scholars are increasingly recognizing their value in complementing knowledge derived from direct observations of climatic parameters (Hasan and Kumar 2020). Efforts are underway to combine scientific observations with public perceptions to enhance understanding and reduce uncertainty in adaptation planning (Ricart et al. 2022). Several studies, such as Shrestha et al. (2019); Imran et al. (2020) and Roy et al. (2021) have compared farmer perceptions with measured climate data. Globally and in Africa, there is both agreement for, e.g., Hasan and Kumar, (2019) and contradiction between perceptions and measured climate data for, e.g., Paul et al. (2023) shaped by factors such as exposure, livelihood dependence, and access to information (Hasan and Kumar 2019). While discrepancies highlight the need for better spatial and temporal resolution in climate studies, perceptions data provide invaluable insights into localized impacts, cultural dimensions, and adaptive responses. However, in many parts of rural Africa, instrumental records of climate are limited (Dinku 2019). Local perceptions therefore provide a strong basis to ascertain change in climate variables. Therefore, there is need for more of these comparative studies to offer opportunities to validate scientific data by providing first-hand insights into the knowledge and thought processes of local communities about their physical environment.

Soubry et al. (2020) note a persistent tendency to view African communities especially rural dwellers as passive subjects of climate impacts, despite them having deep local knowledge of weather and climate gained through lived experience, which has supported adaptation (Leal Filho et al. 2022). This knowledge of seasons, storms, and wind patterns guides decisions on farming and livelihoods. Integrating such insights enriches understanding and fosters climate policies grounded in local realities. This raises key questions about how scientific and local knowledge systems can be effectively integrated to inform future mitigation and adaptation efforts. Accordingly, this paper compares rural residents' knowledge and perceptions of climate change with meteorological data, exploring pathways for integration and policy relevance.

Comparison of observed and perceived climate change in rural South Africa

Over the past decades, notable shifts in South Africa's weather patterns have been observed, including fewer rainy days and more frequent droughts and floods (MacKellar et al. 2014; van Wilgen et al. 2016). Climate projections indicate continued increases in temperature and rainfall variability toward 2100 (DEA, 2013; Mastrorillo et al. 2016). Several studies have examined rainfall and temperature trends across South Africa but rarely included perceptions of change. For example, Strydom et al. (2020) analyzed trends in KwaZulu-Natal, Mahlalela et al. (2020) focused on the Eastern Cape, Wolski et al. (2021) on the Western Cape, (Dube and Nhamo 2020) on the Kruger National Park, and (Van Der Walt and Fitchett 2021) covered the entire country.

In parallel, several studies have also examined local perceptions of climate change in South Africa. Among these, Rankoana, (2018) and Talanow et al. (2021) explored perceptions but did not link them with meteorological observations. Rankoana, (2018) found that variations in temperature and rainfall were perceived to have significant impacts on indigenous livelihood resources such as subsistence farming, water availability, and biodiversity in rural Limpopo province. Talanow et al. (2021) found that Western Cape farmers recognized long-term shifts and adopted adaptive practices such as crop rotation and water conservation, though institutional and biophysical barriers constrained broader adaptation.

In contrast, Elum et al. (2017), Gandure et al. (2013), and Kom et al. (2020) linked perceptions with meteorological data. Elum et al. (2017) found significant changes in climate parameters aligned with farmers' observations in Gauteng, Limpopo and Mpumalanga provinces, leading to adaptive strategies such as planting drought-tolerant crops, despite challenges like limited access to irrigation and insurance. Gandure et al. (2013) showed how socio-economic and political factors shaped adaptation strategies, with rainwater harvesting emerging as a widely supported and effective approach. Kom et al. (2020) analyzed responses to climate variability in Limpopo's Vhembe District, revealing that decreasing rainfall and rising temperatures significantly influenced adaptation strategies such as crop diversification, irrigation, and migration.

However, most of this research centers on farmers, neglecting non-agricultural households whose livelihoods are also affected by climate risks. This represents a critical gap, as rural South Africa is experiencing deagrarianisation a shift away from farming toward diverse livelihood strategies (Hebinck 2018; Rusere et al. 2025a; Shackleton et al. 2019). As a result, understanding how different household types perceive and respond to climate change is vital for inclusive adaptation policy. Addressing this gap, our study compares observed climate trends with local perceptions in rural South Africa, where climate change exacerbates health, food, and water insecurity. By linking meteorological data with lived experiences, we provide insights into how scientific and local knowledge intersect or diverge. This integration supports more context-specific adaptation strategies that reflect the realities of increasingly diversified rural livelihoods.

Study site

The study was carried out in the Agincourt Health and Socio-Demographic Surveillance System (AHDSS) site of the Medical Research Council-Wits University Rural Health and Health Transitions Research Unit, in Bushbuckridge, Mpumalanga Province, South Africa (Kahn et al. 2012). The study area experiences a subtropical summer-rainfall climate, with a long-term average annual precipitation of approximately 878 mm, most of which occurs between September and April. The area's long-term average temperature is around 23.3 °C (Rusere et al. 2023). Rainfed subsistence agriculture and natural resource harvesting remain central to household food security (Rusere et al. 2026, 2025b). Although all villages have access to piped water, supply reliability is inconsistent (Hove et al. 2023), and many households rely on rainwater harvesting or the use of nearby dams and rivers during supply interruptions. Consequently, variations in rainfall and temperature directly affect agricultural productivity, resource availability, water security, and overall livelihood stability.

Data

For this study, meteorological data from 1982–2023 were obtained from the Skukuza meteorological station, managed by the South African Weather Service (SAWS). Located less than 30 km from the study area (Manyuchi et al. 2023), the station provides daily records of rainfall and minimum and maximum temperatures. In 2022, we also conducted 10 focus group discussions (FGDs) across 10 villages within the AHDSS to gather local residents' perceptions of rainfall and temperature patterns, including frequency of droughts, extreme heat occurrences, and general landscape changes over the past decade and earlier. During the discussions, participants were first asked whether they perceived any changes in environmental conditions over time. Those who indicated that changes had occurred were then invited to elaborate on the specific aspects of the environment they perceived to have changed. This open-ended follow-up question prompted participants to reflect on environmental transformations and led to detailed accounts of perceived changes in rainfall patterns, temperature, and broader landscape conditions. Additionally, from November to December 2023, a quantitative social survey using a structured questionnaire yielded data from 245 households in 12 villages. Information was collected on perceived changes in temperature and rainfall as well as details on any associated impacts.

Analytical approach

Analysis of perceptions of seasonal climate regimes

All focus group discussions were recorded and fully transcribed after participants voluntarily provided oral and written consent. Using MAXQDA, we first coded the transcripts to extract relevant climate and weather information. In the second round of reading, we focused on extracting text related to changes in climate or weather. This process resulted in detailed scripts highlighting perceived changes in rainfall and temperature patterns as well as perceived trends, including the frequency of droughts and heat waves.

For the survey data, we identified clusters of perceptions via principal component analysis (PCA) and cluster analysis were used to identify distinct classes within the data, aiming to create relatively homogeneous groups that differ significantly from one another. PCA was performed on a correlation matrix constructed from four climate-related variables reflecting perceived changes in rainfall, the frequency of droughts, floods, and heat waves. Each variable consisted

of ordinal categorical responses describing the perceived increase in frequency or intensity of the respective climatic variables. To facilitate the application of PCA to categorical survey responses, all variables were first converted into factors and then transformed using one-hot encoding. This process produced 16 binary indicators representing different climate perception variables. One-hot encoding is a commonly used approach for handling categorical data, where each category is represented as a separate binary variable (Potdar et al. 2017). For a variable with d distinct categories and n observations, the method generates d new binary variables, each with n observations, indicating whether a given category is present (1) or absent (0) for each observation (Lantz 2013). The PCA was conducted on these 16 binary indicators to identify dominant patterns in perceived climate variability. Based on the Kaiser criterion (eigenvalues > 1), six principal components were retained, explaining 82% of the total variance.

Following PCA, hierarchical cluster analysis with Ward's linkage method was applied to group similar response patterns. The derived clusters were evaluated using Fisher's exact and Pearson's chi-squared tests to identify significant differences across respondent characteristics. Clusters were subsequently labeled to reflect varying levels of perceived severity and frequency of climate changes.

Analysis of observed rainfall and temperature data

Rainfall and temperature data from Skukuza station were analyzed for trends and variability. The wet season was considered as ranging from September-April, corresponding to months with substantial rainfall, and the dry season from May–August characterized by low precipitation (Roffe et al. 2020). We employed the non-parametric Mann–Kendall (MK) trend test (Mann, 1945; Kendall, 1975) to assess seasonal trends in total rainfall, number of wet days, length of maximum dry spells in a month, average number of dry spells, minimum temperature (Tmin), maximum temperature (Tmax) and mean temperature (Tmean). Drought conditions were quantified using the Rainfall Anomaly Index (RAI) developed by van Rooy (1965) with the RAI values greater than − 0.50 indicating no drought; between − 0.54 and − 0.84, indicating mild drought, − 0.84 and − 1.00 moderate drought and less than − 1.00 severe drought. We measured the number of wet days as well per season (days with rainfall > 1 mm). Extreme daily rainfalls were also investigated using the generalized extreme value (GEV) distribution to derive return periods and the corresponding values. The GEV distribution encompasses the three classical extreme value distribution types: Gumbel, Weibull and Fréchet (Coles 2001; Jenkinson 1955). The GEV approach is typically applied to block maxima, i.e., the maximum value observed within a specified time interval, commonly one year. In this study, we used annual maximum daily precipitation for each year. In addition, dry days (days with rainfall < 1 mm) during the wet season were assessed with focus on dry spell episodes > 10 days and the precipitation records during the next 10 days. A dry spell in the framework of this study is defined as a sequence of consecutive uninterrupted dry days during the rainy season (Mzezewa et al. 2010). The probability of experiencing dry spells ≥ 10 days in the four decades under study (1982–1991, 1992–2001, 2002–2011, 2012–2021) was derived based on the empirical cumulative distribution function.

Furthermore, we categorized temperature extremes as warm days (Tmax 25–30 °C), hot days (Tmax 30–35 °C), and very hot days (Tmax ≥ 35 °C). The MK trend test was applied to assess trends in rainfall and temperature extremes, with significance set at the 5% level. In this study, we also determined the onset of rain, cessation of rains and rainy season duration using Skukuza station data. The onset of rainfall was defined as the first day from September of each summer rainfall season when at least 25 mm has accumulated over the preceding 10 days, along with an additional 20 mm over the following 20 days. This criterion, widely applied in southern Africa's summer rainfall regions, ensures adequate moisture for maize germination and early crop growth (Reason et al. 2005; Tadross et al. 2005). Rainfall cessation was determined as the first day after 1 st March when the cumulative rainfall over 30 consecutive days is less than 10 mm (Kabanda and Nenwiini 2016). The length of the rainy season was determined by subtracting the Julian day of the start of rainfall from 365 (or 366 for leap years) and then adding the Julian days of the end of the season, provided the start of the rains occurs before December 31. If the rainy season began in January or later, the duration was simply calculated by subtracting the start Julian day from the end Julian day. Rainfall variability was evaluated using the coefficient of variation (CV), which was categorized as low (CV < 20), moderate (20 ≤ CV < 30), or high (CV ≥ 30). Finally, we contrasted the climate data analysis with participants' perceptions from the focus group discussions, analyzed through MAXQDA, and with perceptions from the quantitative social survey analyzed using the "gt" package in R.

Results

Perceived seasonal climate regimes: qualitative and quantitative evidence

Shifts in rainfall timing and seasonal structure

Participants consistently reported a shift in the onset and duration of the rainy season. Traditionally, rainfall occurred

between September and December, with a brief spell in January before resuming. These patterns guided key agricultural activities such as ploughing and planting. However, participants described a marked delay and shortening of the rainy season, with rainfall now occurring later in the year and outside expected periods.

One participant explained:

> We used to plough from September to December because it would rain during those months. But now, since the seasons have changed, we are no longer getting rain during that time.

Another participant highlighted the altered rain patterns:

> Now, the rain comes in May, June, and July, followed by winds in August. There is now much less rain compared to the past.

These accounts indicate a perceived change in rainfall from established seasonal calendars, disrupting agricultural planning.

Increasing rainfall variability and declining reliability

Beyond shifts in timing, participants emphasized increasing unpredictability and interannual variability in rainfall. Good rainfall years were reported to be followed by little or no rain, undermining farming stability.

> In 2020, we harvested a lot, but in 2021, there was no rain, and we didn't get anything. During the rainy season, we don't receive rain.

An older participant also emphasized a long-term decline in rainfall reliability, contrasting current uncertainty with historically dependable conditions.

> In the old days, we didn't have complaints about rainfall because it occurred reliably and was sufficient for crop production. This allowed us to prepare our farms and start planting maize and vegetables without any worries. Nowadays, there is no reliable rainfall, and it has declined.

These narratives collectively point to a perceived transition from stable and predictable rainfall to highly variable and unreliable patterns.

Changes in rainfall intensity and extremes

Participants further reported a shift in rainfall characteristics from steady, moderate rains to short, intense events often associated with strong winds and flooding, followed by prolonged dry spells.

One participant described:

> Previously, rain would come in showers. Now, the rain comes in large amounts with strong winds followed by dry spells.

This reflects a perceived increase in rainfall intensity and intra-seasonal variability, compounding agricultural challenges.

Rising temperatures and increasing climate extremes

In addition to rainfall changes, participants widely perceived increasing temperatures, particularly more intense heat during summer. These changes were linked to broader climate-related challenges, including droughts and floods.

As participants noted:

> During the summer season, it's very hot, almost abnormal. It was hot before, but now it's even hotter.

Participants also recalled historical droughts (e.g., 1992) and reported that droughts and heatwaves have become more frequent over the past decade, suggesting heightened exposure to climate extremes.

As one participant pointed out that:

> The unusual heat started from 1991 and 1992 but occurred sometimes and even now it sometimes happens. So, 1992 was just the beginning or an alert that going forward we would experience unusual heat from the sun, but it did not occur every year. Back in the days, our grannies would say they had never experienced such heat waves during their youth.

Perceived drivers of climate change

While many participants expressed uncertainty about the causes of these changes, some attributed them to human activities and cultural shifts**,** including environmental degradation and the erosion of traditional practices.

Another participant remarked:

> When it comes to rain, we are experiencing a big change because it's no longer raining during the rainy season. We believe this is happening because we have lost our culture and no longer follow those cultural rules.

This highlights the role of local explanatory frameworks in shaping climate perceptions.

Integration with quantitative findings

These qualitative results are strongly supported by the quantitative results. The Hierarchical Cluster Analysis (HCA) identified three perception groups based on the dendrogram (Supplementary material Fig. 1). Table 1 describes each cluster based on the

attributes used to label them. Cluster 1 consists of participants who perceived severe changes in rainfall, frequent drought and increasing occurrence of high temperatures and increased flood events. This was the biggest cluster with 50.2% of respondents. Cluster 2 consists of participants that perceived moderate changes in weather patterns, including increases in occurrence of droughts, temperature extremes, and floods, though not as severe as Cluster 1. Forty percent of participants fell into this cluster. Participants in cluster 3 perceived no changes in weather patterns, including no changes in occurrence of droughts, temperature extremes, and floods. These participants were in the minority, constituting only 9.8% of respondents. Overall, participants perceived a clear shift from predictable, moderate, and reliable seasonal climate regimes to delayed, shorter, and more variable rainfall seasons, coupled with increasing temperatures and more frequent extreme events. These changes have disrupted agricultural calendars, reduced farming reliability, and increased livelihood uncertainty.

Weather station rainfall and temperature data characteristics

The descriptive statistics of rainfall and temperature for Skukuza from 1982–1983 to 2022–2023 wet seasons reveal notable patterns in seasonal variability (Table 2).

Rainfall: The average rainfall during this period is 521.39 mm per season (September-April), with a standard deviation of 199.60 mm, indicating substantial variability. Over the past three decades (1992–2001, 2002–2011, and 2012–2022), dry seasons from May to August have consistently exhibited lower rainfall compared to the baseline period of 1982–1991. Similarly, the average rainfall recorded in September and October during these three decades has been consistently lower than that observed in 1982–1991, further highlighting a decline in precipitation during the start of the growing season (Fig. 1). Trends in RAI, rainy days, and rainy days≥ 50 mm: The trend analysis of the Rainfall Anomaly Index (RAI) exhibits a minimal decreasing trend (tau = − 0.13) (Fig. 2a), suggesting a potential increase in negative anomalies, though the shift is not significant. The trend showing a decrease in the number of wet days (Fig. 2b), particularly those with significant rainfall, across the observed period, may reflect broader changes in the region's climate, contributing to increased variability and potentially exacerbating drought conditions during seasons with fewer rainy days. Similarly, the number of rainy days with 50 mm or more of rainfall (Fig. 2c) shows a moderate a very slight decrease (tau = − 0.02).

Table 1 Clusters highlighting the quantitative extent and intensity of perceived changes in seasonal climate regimes among households in Mpumalanga, South Africa

Characteristic	Perceived severe climate changes 1, $N=123$	Perceived moderate changes 2, $N=98$	Perceived no changes 3, $N=24$	p-value[1]
Change in rainfall, %				< 0.001
No changes	0%	0%	9.80%	
Minimal change	0%	1.22%	0%	
Moderate change	2.45%	36.32%	0%	
Extreme change	47.76%	2.45%	0%	
Drought occurrence frequency, %				< 0.001
No changes	0%	0%	9.80%	
Low increase	10.20%	16.33%	0%	
Moderate increase	17.14%	22.04%	0%	
Very high increase	22.86%	1.63%	0%	
Extremely high temperatures and heat waves, %				< 0.001
No changes	0%	0%	9.80%	
Slight increase	0%	2.45%	0%	
Moderate increase	0%	13.06%	0%	
Very high increase	50.20%	24.49%	0%	
Frequency of occurrence of floods, %				< 0.001
No changes	0%	0%	9.80%	
Slight increase	28.16%	17.55%	0%	
Moderate increase	16.73%	21.22%	0%	
Very high increase	5.30%	1.22%	0%	

[1]Fisher's exact test; Pearson's chi-squared test

Table 2 Mean monthly and seasonal rainfall and temperature over Skukuza from 1982– 1983 to 2023– 2024

Month	Rainfall				Temperature			
	Mean	SD	CV	MK	Mean	SD	CV	MK
September	15.36	19.70	1.28	− 0.04	21.76	1.11	0.05	0.21
October	35.40	26.07	0.74	− 0.24*	23.86	1.45	0.06	0.26*
November	82.15	63.85	0.78	0.00	25.01	0.96	0.04	0.05
December	97.08	56.05	0.58	− 014	26.17	1.18	0.05	0.28*
January	99.26	83.28	0.84	− 0.13	26.54	0.79	0.03	−0.04
February	91.24	103.14	1.13	0.02	26.59	1.04	0.04	−0.01
March	63.60	51.29	0.81	− 0.18	25.58	1.02	0.04	0.06
April	37.30	41.23	1.11	− 0.06	22.99	1.21	0.05	0.03
Seasonal	521.39	199.60	0.38	− 0.07	24.77	0.59	0.02	0.16

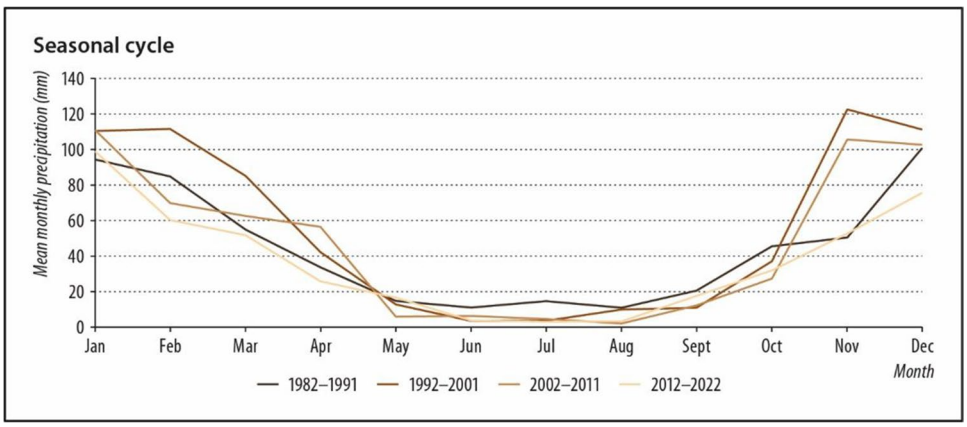


Fig. 1 Mean monthly rainfall illustrating the seasonal cycle

Figure 3a shows that the average onset of rainfall typically occurs around Julian Day 282, aligning with the first dekad of October. Early onsets have been recorded as early as the first dekad of September, while late onsets extend to the first dekad of February. Similarly, Fig. 3b indicates that the average cessation of rainfall falls around Julian Day 93, corresponding to the first dekad of April. The earliest cessation dates are observed in the first dekad of March, while the latest extend into the last dekad of April. On average, the rainy season lasts 159 days. The Mann–Kendall (MK) test revealed no significant trends in the timing of rainfall onset, cessation, or the duration of the rainy season over the observed period. The coefficient of variation (CV) for onset dates, cessation dates, and rainy season length were 22%, 23%, and 24%, respectively, indicating moderate variability. While these findings suggest a potential shift toward drier conditions in the region, the absence of significant trends indicates that the observed changes are neither strong nor consistent enough to reach definitive conclusions.

The empirical cumulative distribution function (ECDF) shows that the probability of dry spells lasting ≥ 10 days declined from 1982–1991 to 1992–2001, but increased again in the last two decades, approaching earlier levels (~ 0.20) (Table 3). To contextualize rainfall responses to these events, rainfall amounts were classified by magnitude based on the density distribution (Supplementary material Fig. 3), with dry spells ≥ 10 days defined as extreme. Rainfall following these extreme dry spells (≥ 10 days) is typically not characterized by single very heavy events (> 50 mm), but rather by substantial cumulative rainfall over a 10-day period (Fig. 4). Notable exceptions include the 1992/93 and 1995/96 seasons, where extreme single-day and cumulative rainfall totals exceeded 100 mm and 250 mm, respectively (Fig. 5). Since 2018, however, cumulative rainfall after extreme dry spells has generally been lower, with fewer heavy rainfall events observed. Return period analysis indicates that rainfall magnitudes of 67 mm, 91 mm, 106 mm, and 133 mm correspond to 2-, 5-, 10-, and 50-year events, respectively, with decreasing probabilities of occurrence (Supplementary material Fig. 4). Overall, recent decades have experienced several high-return-period rainfall events, including rare back-to-back extremes in 2012–2013, highlighting increasing variability in rainfall patterns.

Temperature: The seasonal mean temperature, standard deviation (SD) and coefficient of variation (CV) values for monthly and seasonal characteristics are presented in Table 2 below. The mean temperature reveals a seasonal pattern with warmer temperatures peaking from November to February.

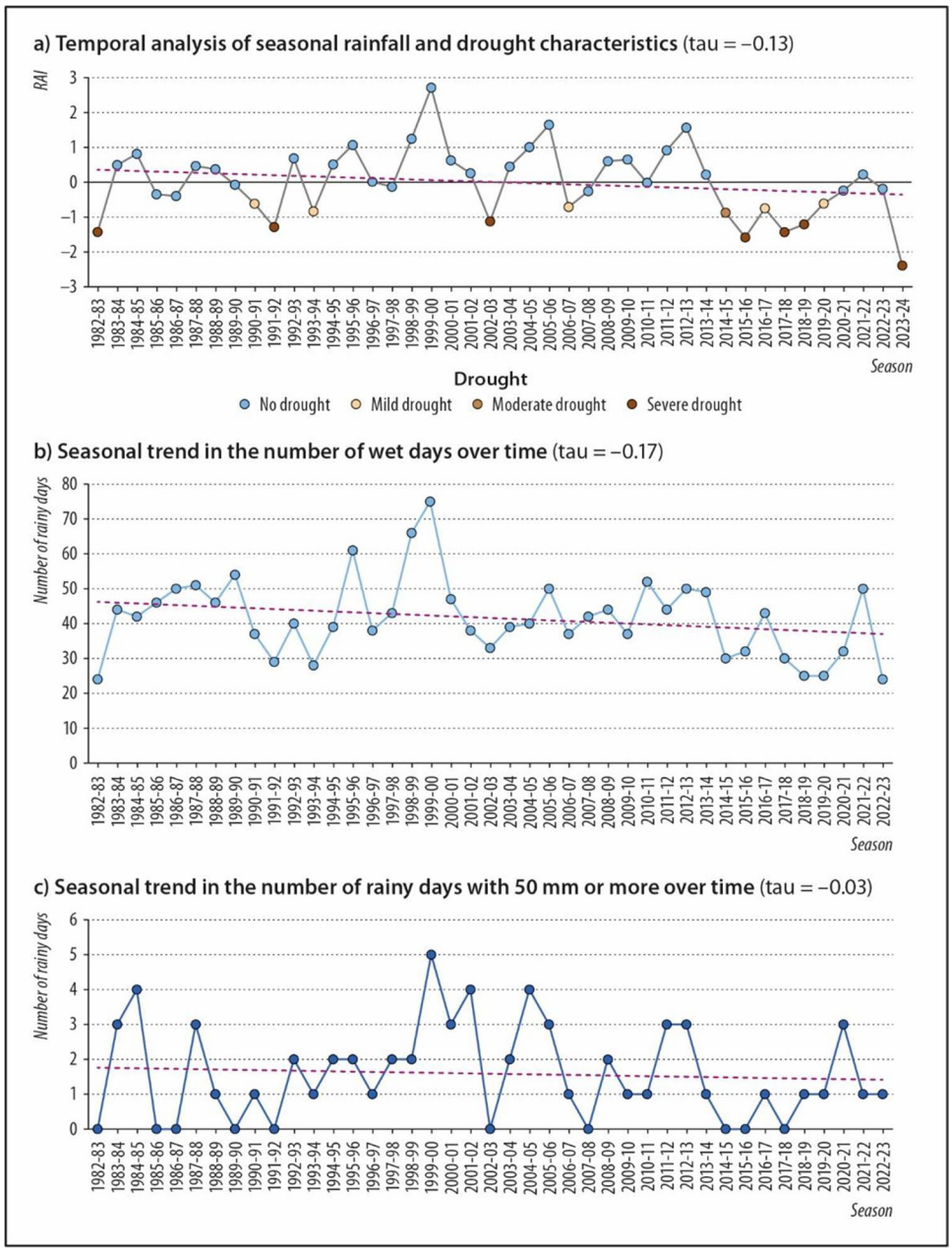


Fig. 2 Skukuza weather station rainfall trends. **a** Temporal variability in seasonal rainfall and drought characteristics; **b** trends in the number of wet days per season; and **c** trends in the frequency of heavy rainfall events (≥ 50 mm) per season

Notably, there is a significant positive trend in October and December, indicating increasing mean temperatures during these months, while other months show more stable trends (Table 2). There is a notable increase of maximum temperature over the seasonal period 1982–1983 to 2022–2023 (Fig. 6a. In general, the frequency of warm days is decreasing (Fig. 6b) while the frequency of hot days (Fig. 6c) and frequency of very hot days is increasing (Fig. 6d). These trends reflect the typical climatic progression of the region, characterized by increasing temperatures and a gradual decrease in rainfall during the summer season.

Comparison of perceptions and weather station climate measures

The comparison between weather station climate measures and community perceptions reveals that local residents have a nuanced experience of changes in rainfall characteristics and seasonal regime shifts (Tables 4 and 5). While a non-significant decline and increased variability in seasonal rainfall was reflected in weather station data (MK $p > 0.05$) and (CV = 0.41), 89% of survey participants reported moderate to severe changes in rainfall

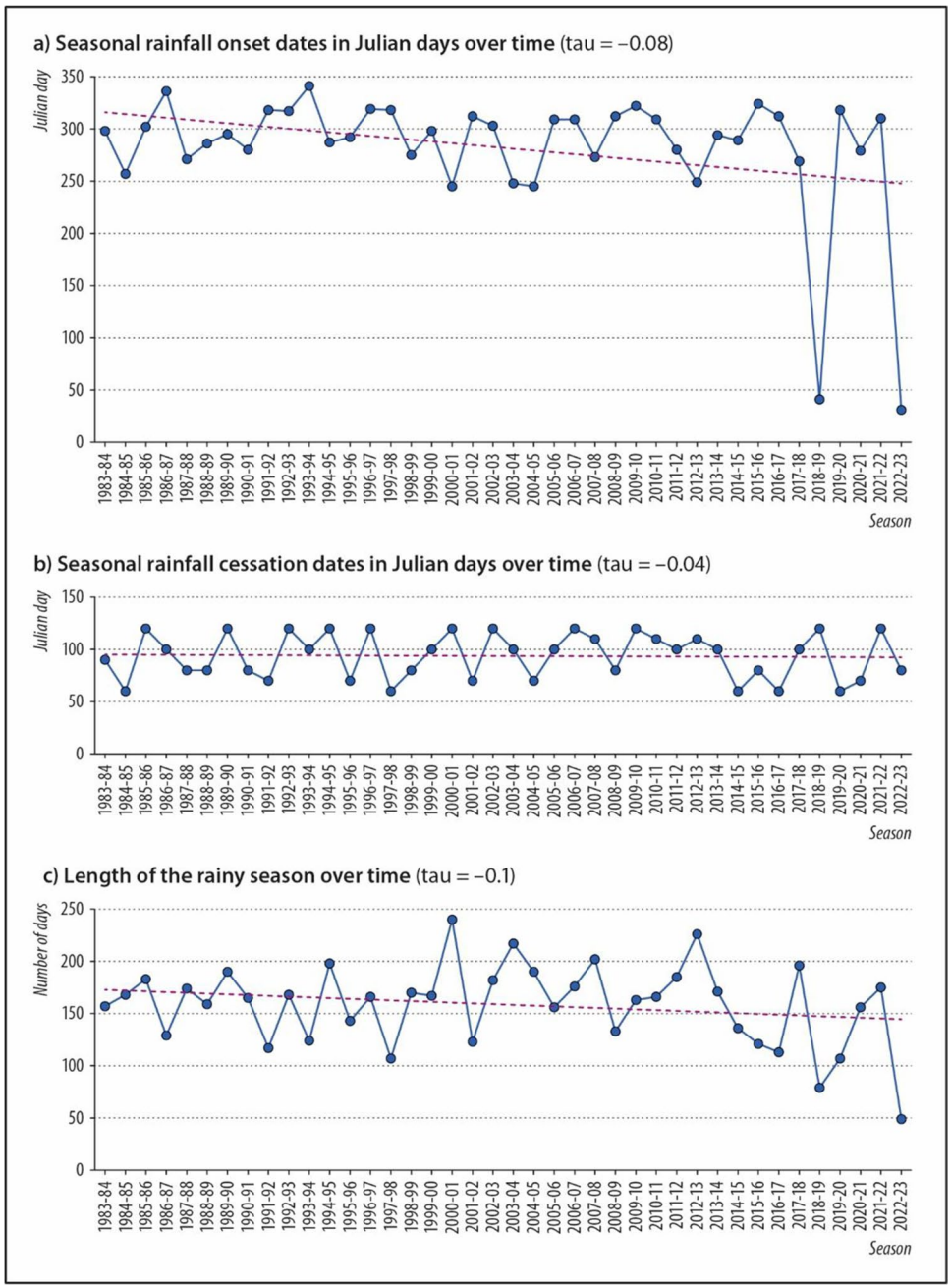


Fig. 3 Rainfall season characteristics. **a** Trend in onset date, **b** trend in cessation date, and **c** trend in the length of the rainfall seasons

Table 3 Probability of dry spells ≥ 10 days

Decade	Probability
1982– 1991	0.20
1992– 2001	0.16
2002– 2011	0.18
2012– 2022	0.19

patterns. Focus group participants noted that rainfall has declined and is no longer reliable. Similarly, a significant decrease in the number of wet days (MK $p < 0.05$) may explain the idea of non-reliable rainy seasons and convey local perceptions of changing seasonal patterns. The station data and focus group discussions show alignment in their observations of rainfall onset. The weather station data indicated that the onset of rainfall typically occurs around Julian Day 282 (first dekad of October), with variations ranging from as early as September to as late as December or February. Similarly, participants in focus group discussions noted that while rain was traditionally expected between September and December, recent years have seen delayed onsets, with rains beginning as late as February.

Table 4 Dates of extreme rainfall events, their magnitudes, and estimated return periods (1992– 2020)

Date	Extreme rainfall value (mm)	Type of extreme, return period
12/12/ 1992	99.5	More than 5 years
01/08/ 1995	102.5	More than 5 years
01/22/ 2004	126	More than 10 years
11/14/ 2004	115	More than 10 years
03/02/ 2006	94.5	5 years
12/28/ 2008	92	5 years
04/04/ 2010	91.6	5 years
01/17/ 2012	119.6	More than 10 years
01/18/ 2012	140.4	More than 50 years
01/18/ 2013	133.2	50 years
02/09/ 2020	93.8	5 years

High temperatures have increased significantly (MK $p < 0.05$), with qualitative reports emphasizing an almost "abnormal" increase in heat during both summer and winter. Despite a non-significant rise in the number of hot and very hot days (MK $p > 0.05$), 88% of participants perceive a marked increase in extreme temperature occurrences. Moreover, the number of years per decade with a RAI < -1 has increased since 1982, from one to three in the past decade 2012–2023. The combination of this with the substantial number of participants perceiving an increase in extreme temperature events, may explain the fact that 65.36% of participants also perceive a rise in drought frequency. However, it should be clear that high temperatures, or negative anomalies < -1 do not solely and always characterize drought. However, despite a non-significant decline in extreme rainfall events (MK $p > 0.05$), 56.9% of participants observed some changes in floods and extreme rainfall, with focus group participants pointing out a shift in rainfall patterns with intense but short-lived showers replacing prolonged light rains.

Discussion

In this study, we examined and compared local perceptions of climate change alongside weather station climate data on temperature and rainfall to better understand the extent of climate change and in Bushbuckridge, Mpumalanga. This study demonstrates that local perceptions of changes in rainfall characteristics and seasonal regime shifts in Bushbuckridge strongly reflect climate variability rather than changes in absolute rainfall totals. Specifically, there is clear alignment between local observations and meteorological data with respect to rising temperatures and declining wet-day frequency, while perceptions of declining rainfall amounts show weaker agreement with measured trends. This suggests that communities are more attuned to shifts in the timing, intensity, and distribution of rainfall events features that directly shape lived experiences than to long-term changes in cumulative rainfall. This is in agreement with findings from a review by Soubry et al. (2020), which showed that in the global South, 87% of studies comparing farmers' perceptions with historical climate data found those perceptions to be accurate. Both local perceptions and weather station data in our study indicated rising seasonal temperatures and fewer wet days from 1982–1983 to 2022–2023. These results further align with similar findings from Kom et al. (2020) in rural Limpopo and Dube and Nhamo (2020) in the nearby Kruger National Park. Participants' observations of increasingly hot summers and frequent droughts demonstrate their

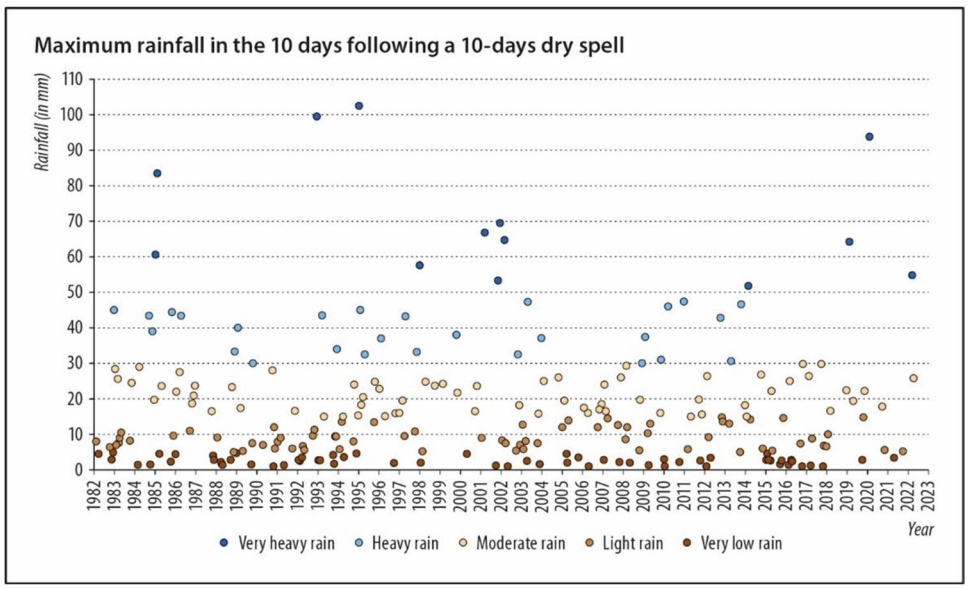


Fig. 4 Maximum rainfall in the 10 days following a 10-day dry spell with 1–5 mm classified very low rain, 5–15 mm light rain, 15–30 mm moderate rain, 30–50 mm heavy rain, and > 50 mm extreme rain

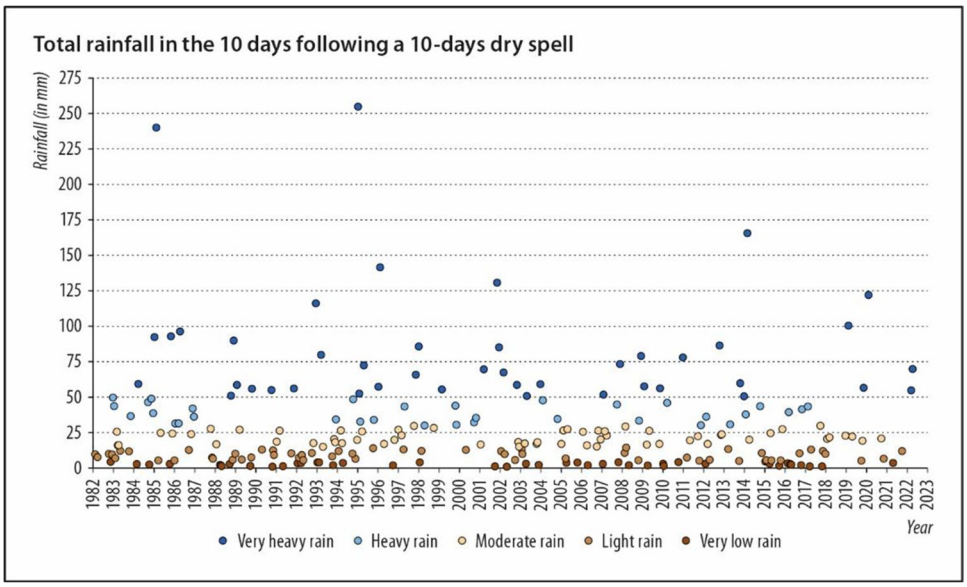


Fig. 5 Total rainfall in the 10 days following a 10-days dry spell

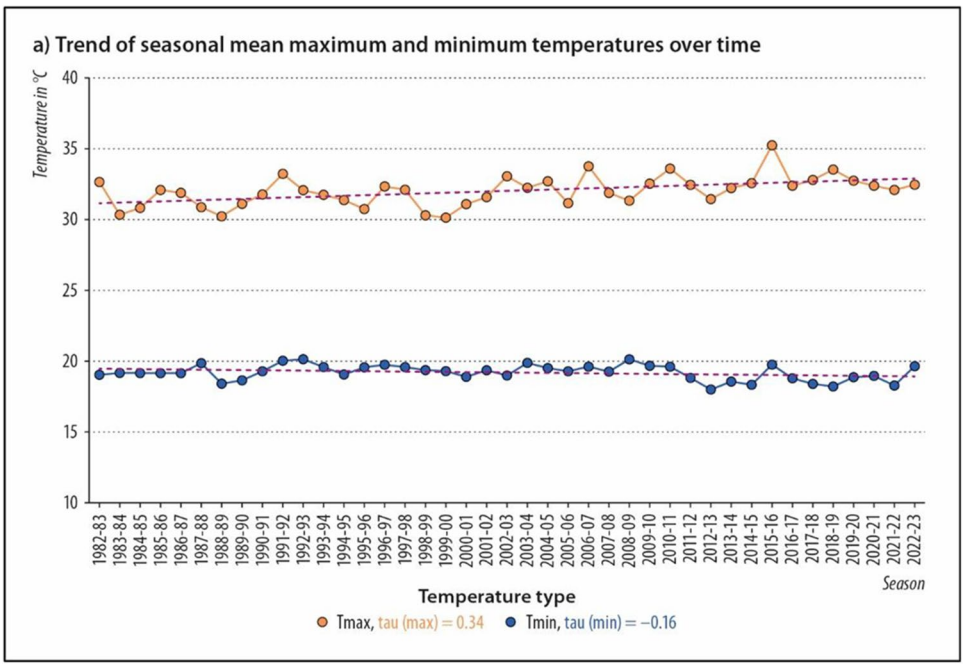
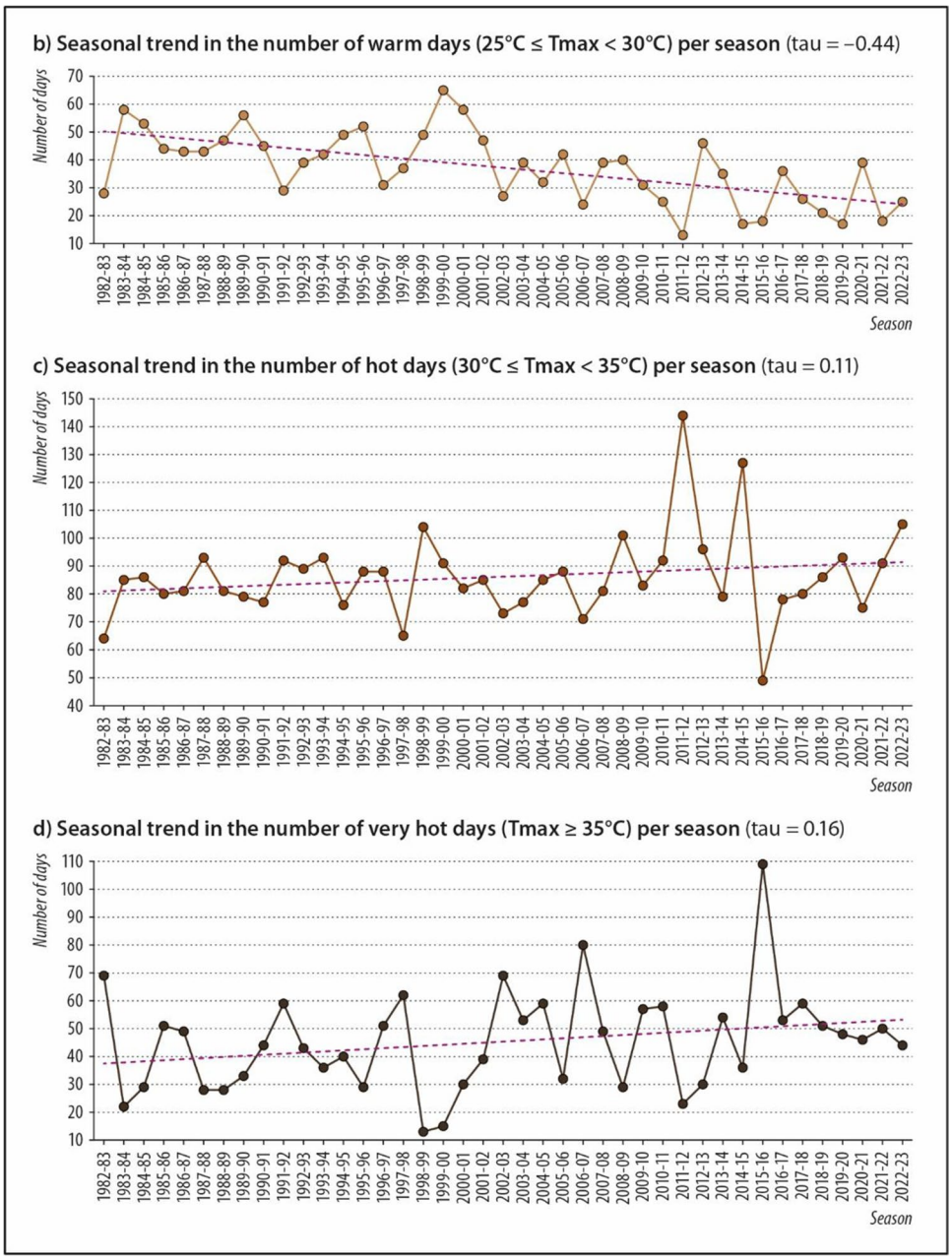


Fig. 6 **a** Trends in minimum and maximum temperatures recorded at Skukuza weather station. **b–d** Seasonal temperature characteristics. **b** Trend in the number of warm days between (25 °C ≤ Tmax ≤ 30 °C). **c** Trend in the number of hot days between (30 °C ≤ Tmax ≤ 35 °C) and **d** trend in the number of very hot days (Tmax ≥ 35 °C)

clear and strong awareness of the magnitude of climate variability and change, even in the absence of meteorological data. The observations from our participants align closely with the findings of Manyuchi et al. (2022), emphasizing the growing awareness of climate variability and its impacts, even in the absence of meteorological data. Manyuchi et al. (2022) work similarly highlights that participants reported, as of 2019, rising temperatures, particularly during summers, over recent years. The weather station rainfall results are further supported by broader regional trends in southern Africa and in South Africa, where studies have shown shifts in wet day occurrences (Thoithi et al. 2021) and rainfall seasonality (Roffe et al. 2021), rather than a straightforward decline in total rainfall. For example, Roffe et al. (2021) highlights trends across South Africa towards late wet-season onset and changes in the duration and intensity of wet-season rainfall over our study area, observations which were alluded by participants.

The study also uncovered discrepancies between perceived and weather station rainfall patterns. While participants reported a significant decline in rainfall and increased variability, the weather station rainfall data did not show a statistically significant long-term decline. Although there was a decrease in the number of wet days, the total rainfall

Fig. 6 (continued)



data did not show a clear overall reduction. This finding corroborates with Huang et al., (2024) who found that farmers' perceptions of rainfall trends are often inaccurate. These discrepancies may arise because residents are more attuned to changes in the timing, intensity, or intra-seasonal distribution of rainfall such as heavier downpours separated by longer dry spells rather than changes in total annual rainfall amounts. These nuanced shifts in rainfall patterns may not be immediately evident in aggregated annual totals or long-term mean values but still represent meaningful changes in climate experienced at the local level. Furthermore, the discrepancies could be due to instinctive judgments (heuristics) based on recent severe weather events, like droughts, as they had experienced three severe droughts in the last decade. In such a case, local residents might also struggle to notice or understand long-term trends in rainfall because it's harder to see patterns that play out over many years. This is referred to as recency bias, a common challenge in climate perception research, whereby recent and particularly impactful weather events tend to shape individuals' assessment of climate trends (Brügger et al. 2021; Fownes and Allred 2019).

However, in such a case, the importance of local residents' perceptions cannot be understated because perceptions shape behaviors, decision-making, and, potentially, anxiety about the future (Huang et al. 2024). For instance, perceptions of increasingly unpredictable rainfall and hotter

Table 5 Comparison of perceived climate change and weather station climate measures

Parameter	Weather station	Quantitative perceptions	Qualitative perceptions
Change in rainfall amount and season duration	Non-significant decline in seasonal rainfall and length of the rainfall season, MK, $p > 0.05$	9.8% of participants perceive no change to minimal seasonal rainfall change while 90.2% perceive moderate to severe to rainfall changes	"In the old days, we didn't have complaints about rainfall because it occurred reliably and was sufficient for crop production. Nowadays, there is no reliable rainfall, and it has declined."
Number of wet days	Significant decline, MK, $p < 0.05$	9.8% of participants perceive no change to minimal seasonal rainfall change while 90.2% perceive moderate to severe to rainfall changes	"We used to plough from September to December because it would rain during those months. But now, since the seasons have changed, we are no longer getting rain during that time."
Onset of the rainy season	The average onset of rainfall typically occurs around Julian Day 282, aligning with the first dekad of October. Early onsets have been recorded as early as the first dekad of September, while late onsets extend to the first dekad of February		"The rainy season has changed from what we normally expected. We used to expect rain around September, but last year it only started in December. I don't know why the rainy season has changed."
High temperatures	Significant increase in maximum temperatures, MK $p < 0.05$		"The challenging part is climate change; for example, during the summer season, it's very hot, almost abnormal. The same goes for winter It was hot before, but now it's even hotter."
Number of hot and very hot days	Non-significant increase hot and very hot days MK, $p > 0.05$	75.56% of participants perceive a very high increase in the occurrence of extreme temperatures while 10.04% of participants perceive no change in the occurrence of extreme temperatures	"The unusual heat started from 1991 and 1992 but occurred sometimes and even now it sometimes happens. So, 1992 was just the beginning or an alert that going forward we would experience unusual heat from the sun, but it did not occur every year. Back in the days, our grannies would say they had never experienced such heat waves during their youth."
Droughts	Three severe droughts occurred in the last decade (2012–12 to 2022–23) compared to one severe drought in each decade since 1982– 1983	65.36% of participants perceive a moderate to a very high increase in the occurrence of droughts	"Over the last ten years droughts have occurred more frequently."
Extreme rainfall events	Non-significant decline in extreme rainfall events (Number of days with rainfall > 50 mm) MK, $p > 0.05$	56.9% of participants perceive no change to minimal increase in the occurrence of floods and extreme rainfall events	"Previously, rain would come in the form of showers, which lasted a long time but did not cause major disruptions to nature. Even during the time of preparing the fields, rain would come in gentle showers, and there would still be water in the rivers. Now, the rain comes in large amounts with strong winds, sometimes causing floods that last for a few days and offer little benefit."
Dry spells	The probabilities of recording dry spells equal to or greater than 10 days in the last two decades show an increase and tend to reach the 0.20 probability observed in the decade 1982– 1991		"These intense rains are typically followed by dry spells, which leave the soil very dry and unproductive"

summers have direct implications for agricultural planning, water management, and household resilience strategies. This view concurs with Abid et al. (2019) who found that local perceptions of climate variability tend to influence behavioral adaptations, such as altering planting times, changing crop types, or adopting water-saving practices. Additionally, the heightened awareness of drought risks and extreme temperatures can have profound psychological impacts. Uncertainty about future climate conditions may exacerbate stress levels, particularly in communities where livelihoods depend heavily on climate-sensitive activities like agriculture. This stress can manifest as anxiety over food security, income stability, and the well-being of future generations. Such psychological burdens not only influence individual and household decision-making but may also have ripple effects on broader community cohesion and adaptive capacity. Addressing these intangible impacts is essential for designing holistic climate adaptation interventions that account for both the economic and emotional resilience of rural communities.

Aligning scientific data with local perceptions of rising temperatures and rainfall variability is crucial for reducing uncertainty in climate adaptation efforts. When scientific data and local perceptions converge, it bolsters confidence in the accuracy of climatic trends and their impacts. This alignment can be incorporated into the design of locally relevant climate adaptation strategies, the development of early warning systems, and community-focused climate change educational programs. For example, integrating local knowledge into climate risk assessments can help identify micro-level vulnerabilities and adaptation priorities that may be overlooked by meteorological models alone.

The divergence observed in total rainfall and perceptions underscores the complexity of local climate dynamics and how they are experienced by people. This divergence can reveal critical insights into micro-level climate dynamics, such as variations in rainfall frequency, intensity, or distribution, that may be overlooked by meteorological trends but are essential for water resource planning and agriculture. Facilitating community dialogues can uncover the reasons behind divergent views, fostering mutual understanding and identifying priorities for collective action. Triangulating these perceptions with scientific data adds further context, enabling the design of strategies that are both evidence-based and locally informed. In rural African regions, where access to formal climate data is often limited (Myeni et al. 2024), incorporating local perceptions alongside scientific data is vital for developing nuanced and area-specific solutions. National climate policies should address the broader challenges these communities face, such as water security and human health risks from rising temperatures, rather than focusing solely on crop production impacts. By integrating diverse local insights into formal climate adaptation frameworks, we can develop flexible, inclusive strategies that address both shared and conflicting perceptions, enhancing their relevance and effectiveness in tackling climate impacts.

This study has some limitations as it relied primarily on meteorological observations from the Skukuza weather station due to the availability of a continuous and complete dataset covering the study period. Although several other stations operated by the Agricultural Research Council (ARC) and the South African Weather Service (SAWS), including Thaba Chweu, Thulumahashe, Koeltehof, Hazyview, and Graskop, are located closer to the study area, the available datasets from these stations contained substantial gaps and were not complete for the full period required for the analysis. For the periods where observations overlapped with the Skukuza dataset, exploratory comparisons indicated a strong correlation in climatic patterns, suggesting that the Skukuza station reasonably reflects the broader macro-climatic conditions of the region. Nevertheless, reliance on a single station may limit the ability to fully capture local micro-climatic variability across the study area. Future studies could benefit from integrating observations from multiple stations or high-resolution gridded climate datasets to further strengthen spatial representation.

Conclusion

This study sought to address the gap between scientific data and local perceptions of climate change, focusing on the interplay between recorded climatic trends and community experiences in Bushbuckridge. By comparing weather station data with local observations, the study aimed to deepen understanding of how these perspectives align and diverge. The findings reveal both convergence and discrepancies between scientific measurements and local perceptions. While weather data highlight increased temperature trends and changes in rainfall patterns, community perceptions add valuable context, emphasizing the impacts of variability and perceived declines in rainfall. These insights underscore the complexity of local climate dynamics and the importance of integrating diverse knowledge systems in climate research. The implications of this work are clear: adaptation strategies must be both evidence-based and grounded in local realities. By acknowledging the physical and perceived impacts of climate change, policies can become more inclusive and effective. For rural communities like those in Bushbuckridge, incorporating local knowledge into climate risk assessments and adaptation frameworks can help address vulnerabilities more comprehensively. Future research should focus on systematically integrating local perceptions into climate models and policy development to bridge gaps in understanding. Additionally, efforts should explore how community-driven insights can enhance early warning systems, resource management, and resilience-building initiatives. This approach can foster more culturally relevant, equitable, and sustainable responses to the challenges of climate change.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10113-026-02591-1.

Acknowledgements We thank the SAMRC/Wits Rural Public Health and Health Transitions Research Unit, School of Public Health, University of the Witwatersrand, for their invaluable contributions to data collection.

Author contribution F.R., L.H., W.T., C.S designed and sought funding for the research; F.R. collected data; F.R., S.M., N.R.M., G.S., analyzed data with input from W.T., C.S., L.H., and F.R. wrote the paper with input from all the coauthors.

Funding Open Access funding enabled and organized by Projekt DEAL. The authors are grateful for the funding received from the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy (EXC 2052/1–390713894).

Data availability Data collected and analyzed for this study is available upon request to the authors.

Declarations

Ethical approval Ethical approval for this study was obtained from University of Witwatersrand Human research ethics committee (non-medical) [H22/07/47].

Competing interests The authors declare no competing interests.

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