Journal of Arid Environments xxx (xxxx) xxxx

Contents lists available at ScienceDirect

Journal of Arid Environments

journal homepage: www.elsevier.com/locate/jaridenv

Using farmer-based metrics to analyze the amount, seasonality, variability and spatial patterns of rainfall amidst climate change in southern Ethiopia

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ARTICLE INFO

Keywords:
Rainfall
Variability
Ethiopia
Climate change

ABSTRACT

Climate change will likely impact rainfall characteristics in particular locations; the amount, seasonality, variability and spatial patterns. In developing countries, this presents challenges for rural smallholder farmers as their livelihoods are largely based on rain-fed practices. Changes in climate patterns could increase farmers' vulnerability and the need for intervention. In this paper, we develop new metrics of analysis motivated by qualitative research with smallholder farmers. Previous research found that farmers' understanding of historical rainfall change is accurate, yet diverge from some research studies. We analyze meteorological station rainfall data using metrics that are familiar to smallholders. Farmers' perceptions of rainfall in southern Ethiopia were explored through interviews conducted in three communities. Our findings identified some forms of convergence, as well as divergence, in farmers' perception of rainfall trends and meteorological station data results. In asking the question 'Why do data based on farmer experiences of rainfall variability differ from meteorological station data?', we show that using existing data and applying farmer-influenced metrics can improve the information shared with farmers. We argue that, under further climate change, it will be increasingly important to convey meteorological information to farmers in ways that are relevant to them and their agricultural livelihoods.

1. Introduction

Climate change has affected various physical characteristics of rainfall (e.g. rainfall amounts), but the nature and significance of these changes vary regionally. Generally, dry land areas have become drier; some wet areas have become wetter; and yet other areas receive less overall rain but experience more intense rainfall events (Trenberth, 2011). In addition to this complexity in the changing physical characteristics of rainfall, the impacts and perceptions of these changes vary for those whose livelihood is intimately linked to rainfall.

There is a commonly identified divergence, or mismatch, in perceptions of changes in rainfall between scientists and farmers (Chambers, 1997). Gill (1991) sought to better understand why farmers' experiences of rainfall differed from the results of contemporary forms of meteorological analysis of rainfall data. In seeking to resolve that conundrum, Gill (1991) focused upon the definition of rainfall terms (e.g. what counts as a rainy day and how that is calculated), as well as one period of time wherein discrepancies existed. Gill (1991) found the apparent disconnect laid not with rainfall events and data but with methods and scales of analysis. Chambers (1997: 146) subsequently argued that farmers' rainfall assessments of rainfall trends over time tended to be more accurate than averaged meteorological station data. The differences, Chambers (1997: 31) suggested, was that scientists utilized "concepts, values, methods and behavior" rooted in training that approached questions much differently than farmers did. Divergent understandings of rainfall was not one of a different reality, but of different means to categorize and analyze that reality.

The apparent mismatch between farmers' experiences of rainfall and the analysis of meteorological station data is particularly important to understand in contexts of smallscale, rain-fed agricultural systems.

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https://doi.org/10.1016/j.jaridenv.2019.104084
Received 9 April 2019; Received in revised form 2 September 2019; Accepted 30 November 2019
0140-1963/

Please cite this article as: Logan Cochrane, et al., Journal of Arid Environments, https://doi.org/10.1016/j.jaridenv.2019.104084

While the Sustainable Development Agenda has ambitious goals to eliminate poverty and ensure food security for all, a countervailing force is climate change, which has the potential to push 100 million people into extreme poverty by 2030, particularly those whose livelihoods are reliant upon rainfall in arid and semi-arid areas of the world (Adams et al., 2013; Hallegatte et al., 2016). The majority of Ethiopians live in this precarious space. More than 80% of the nation's approximate population of 105 million are rural dwellers who are reliant upon rainfall for their livelihoods (Loening et al., 2009; World Bank, 2019).

This paper draws upon farmers' perceptions of rainfall trends and utilizes metrics influenced by qualitative data collected with smallholder farmers to pilot different analyses of meteorological station data in southern Ethiopia's Wolaita Zone. In so doing, we seek to identify convergence, or lack thereof, in understandings of rainfall changes. This paper explores meteorological and farmer discourses using various rainfall metrics, assessing whether any determined divergent discourses can be aligned. Rather than assume discrepancies between smallholder farmer experiences and meteorological data are due to poor perceptions, we assume the differences are due to analytical approaches.

We do not set out to prove or disprove scientists' or farmers' understandings of rainfall change. Rather, we aim to explore different approaches to analyzing meteorological station rainfall data, using an analysis approach based upon metrics that are influenced by smallholder farmers. Thus, we do not dispute the findings in the literature, but to complement and expand upon them. This paper raises questions about how research is done; specifically the determination of metrics and analysis approaches. This paper contributes knowledge on farmers' experiences in assessing rainfall, which differs from what has previously been reported in the literature on rainfall studies in Ethiopia. The following section provides context on the so-called scientist-farmer divide (we do not label the meteorological analysis common in the literature as 'scientific' and farmer analysis as not; farmers use evidence in their assessments – in attempting to avoid these labels, we opt for descriptions of the methods utilized). That context is followed by a review of studies on rainfall in Ethiopia. In the methods section, we present the qualitative background, quantitative analysis approach and the study area, followed by the findings and a discussion of the results.

2. Background

2.1. Climatological context

Climate change is not a new phenomenon, with Ethiopia having experienced shifts of rainfall over the long-term (timescales of 1000 or 10,000 years), including variations between wetter and drier periods (Conway, 2000). More recent history has witnessed multiple, seemingly regular, drought periods, some of which have resulted in widespread famine (Pankhurst, 1985; Graham et al., 2012). Assessing more recent changes in Ethiopian climate in response to anthropogenic climate change is difficult due to the country's complex geography (Jury and Funk, 2013) and sparse networks of observations over East Africa (Alexander, 2016).

Based upon available instrumental data, there is some evidence that frequency of drought and extreme weather events have increased (Bewket et al., 2015; Suryabhagavan, 2017). The literature on rainfall in Ethiopia primarily focus on long-term change, based upon mean annual or mean seasonal rainfall calculated from meteorological station data (Adimassu et al., 2014; Cheung et al., 2008; Conway, 2000; Eshetu et al., 2016; Gebrehiwot and van der Veen, 2013; Hameso, 2014, 2015; Megersa et al., 2014; Suryabhagavan, 2017; Tilahun, 2006; Wagesho et al., 2013).

One particular study based on gridded observational data and reanalysis products to determine that over 1948–2006, rainfall in Ethiopia's southwestern region decreased by 0.4 mm/month/year (Jury and Funk, 2013). High elevation areas recorded smaller trends. However, the evidence of trends in rainfall varies with specific regions, observational datasets and the rainfall metric considered. Other studies have analyzed daily rainfall data to assess the frequency of extreme rainfall events (Adimassu et al., 2014; Muluneh et al., 2016; Tilahun, 2006). For example, a study focused on examining indices of precipitation extremes shows spatial variability in observed trends in gridded data over East Africa. In some parts of Ethiopia, evidence shows complex trends, including increasing trends in the number of consecutive dry days (CDD) and maximum one-day rainfall amounts (Rx1day), together with decreases in the number of heavy rainfall events occurring (r95p and r99p) (Gebrechorkos et al., 2019). Bewket and Conway suggest that for Amhara Regional State, “there are no consistent emergent patterns or trends in daily rainfall characteristics” (2007: 1467).

The significance of rainfall changes determined from meteorological observations also depends on the seasons examined. Annual and seasonal foci are the dominant periods of analysis in rainfall studies within Ethiopia. Tilahun (2006) used station data from the National Meteorological Agency to identify rainfall anomalies in arid and semi-arid areas of Ethiopia and found that the occurrence of extreme low rainfall events varied geographically and temporally. Using the same set of years (1970–2009) as Tilahun (2006), Muluneh et al. (2016) analyzed data from thirteen government meteorological stations to assess if the frequency of extreme rainfall events had changed. While the results confirmed an increase in extreme (wet and dry) events, they also suggested that much more nuance is required in the study of rainfall trends, highlighting the localized nature of rainfall patterns due to topography and elevation. Taking a narrower approach, Adimassu et al. (2014) focused upon the relatively homogenous environmental region of the Central Rift Valley and were able to identify some significant changes in rainfall variability in the short rain season (*belg*, March–May). This finding, however, is not consistent with other studies. For example, a study exploring annual and seasonal rainfall by Wagesho et al. (2013), primarily using gridded analyses with model data over a fifty-year period, found regional rainfall declines during the *kiremt* season (June–September) in northern, northwestern and western Ethiopia, with some indications of increases in eastern Ethiopia. The remaining areas, including the region focused upon in this study, were found to have no statistically significant trends (Wagesho et al., 2013).

In general, most studies report similar findings to Conway (2000); that there is “no evidence for a long-term trend or change in the region's annual rainfall regime” (Conway, 2000: 161). Conway (2000) focused on the northeastern highlands, and studies focusing on other regions have found similar results. For example, in assessing monthly rainfall data over a forty-year period, Meze-Hausken (2004) suggested that no seasonal changes are observed in northern Ethiopia. These conclusions have also been made by Cheung et al. (2008), Conway et al. (2004), Rossell (2014) and Tilahun (2006).

Projections of rainfall changes for Ethiopia and the wider East African region are also variable. Cook and Vizy (2013) found a decrease in the eastern Ethiopian spring rainfall season length in an ensemble of global climate models (GCMs). An overall decrease in rainfall during growing season days was reported, and a decrease in the length of boreal spring rains throughout the 21st Century. Decreases in observed rainfall detected by Jury and Funk (2013) were projected to continue in the future in GCMs. Other studies find non-significant trends, and IPCC reports note that there is a high level of uncertainty in model projections of precipitation and high variability among models regarding projections of precipitation in topographically complex regions (eg. IPCC, 2012).

Although these instrumental-based approaches to analyzing rainfall data provide important insights, they also have critical limitations in understanding changes in Ethiopia. First, rainfall is aggregated over time periods, which may render invisible important facets of rainfall for farmers. Since rainfall varies locally due to topography and elevation, station-specific studies may be more effective at identifying localized, community-level, trends and, therefore, more appropriate to support

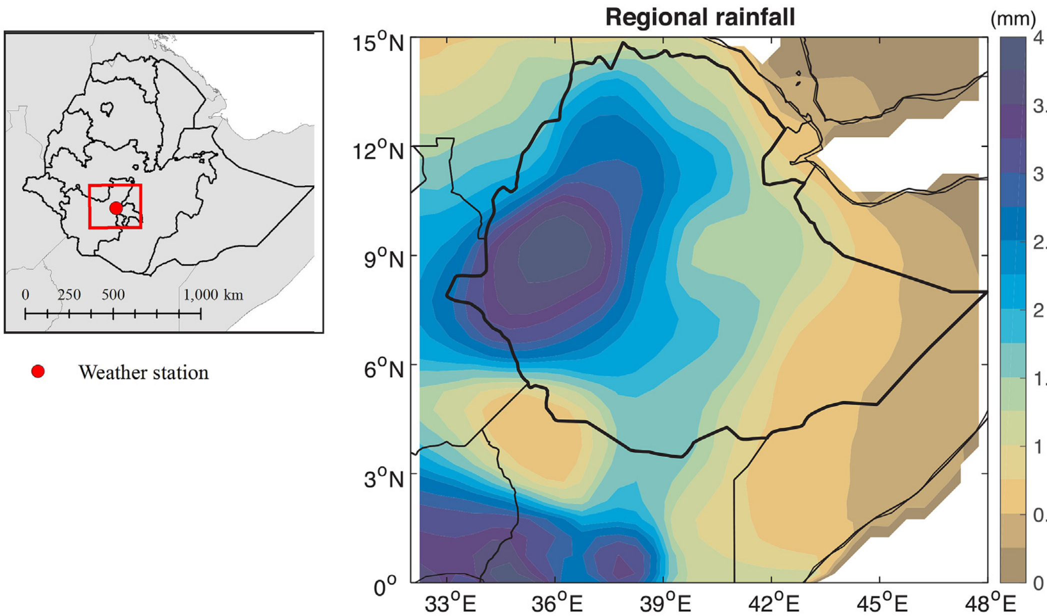

Fig. 1. Average annual regional rainfall (from CPC Global Precipitation data long term mean 1981–2010, mm/day). Left hand panel shows location of the Wolaita Zone, SNNPRS, Ethiopia, and observational weather station.

decision making. However, analyses of local-level meteorological data do not always align with farmer experiences (e.g. Adimassu et al., 2014; Ayal and Filho, 2017; Meze-Hausken, 2004). This is particularly important because analyses made to-date have not been translated into relatable, useable science by decision makers (Kalafatis et al., 2015; Kirchhoff et al., 2013). Nor have the studies, farmers argue, accurately captured their experience of rainfall change (Cochrane, 2017b).

Second, the *impacts* of changes are not revealed through meteorological analysis alone. Increased rainfall will not necessarily benefit the population in those regions. The result may be less consistent rainfall and more frequent extreme weather events. For a nation whose people are largely reliant upon rainfall for their agricultural livelihoods, the expected changes warrant much greater attention. Additionally, there is limited infrastructure in the region that would mitigate the negative impacts of extreme weather events, such as irrigation or flood prevention systems, making the region particularly vulnerable. As noted by Muluneh et al. (2016), there is an increasing need, amidst the diversity of future climate scenarios, for local-level studies that support decision making for both farmers and service providers (Cochrane and Singh, 2017). Regional studies that integrate data from multiple meteorological stations have largely been inconclusive in identifying rainfall trends at the local scale (Cheung et al., 2008; Conway et al., 2004; Rossell, 2014; Tilahun, 2006).

2.2. *Perceptions of rainfall and climate change*

Smallholder farmers are typically more informed than often portrayed – thought of as uninformed, stubborn or backward, including by those tasked to support them (as in Asfaw and Admassie, 2004; also see Cochrane, 2017c). Using tools often developed without farmer input, when research is undertaken farmers are commonly asked to answer questions that are irrelevant to their realities, using inappropriate scales or asked to make irrelevant generalizations (Cochrane, 2017b). For example, when community members have the opportunity to co-produce household surveys they identify the typical, but problematic, framing of questions. Commonly asked survey questions, such as those that refer to the use of agricultural inputs (e.g. improved seed, fertilizer, pesticide), are considered meaningless because decisions regarding the use of inputs are crop-specific and a single answer cannot be generalized to cover their entire agricultural livelihood practices. Similarly, rainfall measures take different forms. Researchers may focus on extreme events and aggregate annual or seasonal rainfall, whereas farmers focus on rainfall onset, duration and variability. As noted by Tilahun (2006: 483) “the effectiveness of rainfall depends almost as much on its timing as on its total during the season”. The available literature does not focus on measures that farmers perceive to be of greatest importance to their livelihoods and decision making.

Other studies have focused upon farmer perceptions of rainfall changes (Bewket et al., 2015; Cochrane and Costolanski, 2013; Hirpa, 2016; Tesfahunegn et al., 2016). The identification of divergences between farmer perceptions and meteorological studies, defined here as differences in understanding rainfall characteristics, is not new to Ethiopia or in similar studies elsewhere (e.g. Adimassu et al., 2014; Ayal and Filho, 2017; Meze-Hausken, 2004). While we recognize the value of annual and seasonal rainfall studies, this differs from how farmers typically assess rainfall.

3. Methods

Our paper starts from two related questions: ‘Do data based on farmer experiences of rainfall variability differ from meteorological station data, and if so, why?’ Rather than focus on aggregating diverse experiences and perceptions, we focus on a point about which farmers are adamant: for farmers, declining rainfall trends are apparent, so why do scientists struggle to identify them? Following Chambers (1997), we do not focus on the existence of a divergence between the two *per se*, but the processes utilized to arrive at them. We have identified how the dominant trends within the academic literature represent particular concepts, values and methods, which differ from those utilized by farmers. Rather than attempt to fit the meteorological station data within farmers' experience, or the converse, we re-analyze the meteorological station data and offer a different interpretation of existing data. Thus, we do not offer an in-depth qualitative study of farmers' perceptions, nor a criticism of the findings in literature. We argue that the approach we apply in analyzing meteorological station data complements and enhances knowledge, and one that attempts to align metrics with how farmers experience rainfall trends. Furthermore, given that much of the data we have cited is out of date from a climatology perspective, it seems well-worth revisiting the available data.

3.1. Study area

The case study is drawn from Wolaita Zone, in the Southern Nations, Nationalities and Peoples' Regional State (SNNPRS) in southern Ethiopia (see Fig. 1). Studying rainfall characteristics in this area of Ethiopia is particularly important because it is exposed to greater variations than other areas. The highlands of Ethiopia tend to experience regular rainfall, and could be considered relatively resilient to rainfall changes. The eastern lowlands consistently experience minute amounts of rainfall and are comparatively more vulnerable to rain changes. Wolaita Zone, on the other hand, fluctuates between excessive and insufficient rainfall, which greatly affects the lives and livelihoods of smallholder farmers in the region. The weather station is managed by the Government of Ethiopia, specifically the National Meteorological Agency, the location of which is marked in Fig. 1 (Sodo town). Data from this station was requested at the federal office of the agency, based in Addis Ababa. The three sites where qualitative data were collected are northeast, located 18, 23 and 38 kms away respectively (all located in Damot Gale District, in the *kebeles* of Adeaaro, Adea Ofa and Buge).

Wolaita Zone is home to about two million residents, and its districts have the highest rural population densities within the country. The vast majority share an agroecological setting and practice a form of agriculture that is based in a set of key root-crops (e.g. enset, taro, sweet potato). These root-crops are crucial for the food security of the region, but are sensitive to moisture stress. Insufficient, inconsistent or excessive rainfall can result in crop failures—so too can pests and crop disease. When this happens, emergency situations can result, requiring food assistance, which can require multiple years of recovery. Due to a general lack of irrigation, and the practice of rain-fed agriculture, rainfall patterns significantly impact yields, harvests, food security, income and overall wellbeing (e.g. ability to access healthcare and education via income from the sale of crops).

3.2. Qualitative study

In 2015 and 2016, the Stages of Food Security methodology was undertaken in selected districts within Wolaita Zone, SNNPRS, Ethiopia (Cochrane, 2017a). That study focused on issues related to food (in) security, and included the co-creation of data collection tools and co-analyses of findings with community members. As a follow-up to that study, additional individual interviews were conducted in three communities in order to gain a better sense of the way in which farmers had experienced climate change, and particularly changes to rainfall and its impact on their agricultural livelihoods. The interviewees were randomly selected, conducted in Wolaita language with the support of an interpreter, recorded and translated. An explicit effort was made to ensure diverse socio-economic experiences were included amongst the interviewees.

This study does not focus on the results of that qualitative data *per se*, but its influence on the methods utilized in this study. Discussed in more detail in the results section, farmers spoke about rainfall in terms of months and with reference to specific dates, such as key religious festivals (e.g. Ethiopian Easter). Farmers explained that they were shifting their crop types because of changes to the onset and duration of the rainfall. For example, in the main planting season (*kiremt*, June–September) farmers have shifted to lower yielding but shorter cycle crops. Although other potential causes for shifts in crop choice were acknowledged (e.g. changes to preferences, market value of the crops, improved market access, promotion by extension services), farmers were nonetheless confident that rainfall played a key role. Farmers did not consider total rainfall as particularly important, annually or seasonally. Based upon this, we have taken an approach to analyzing rainfall on a monthly scale. This choice presents some limitations; daily, weekly or bi-weekly analysis in the future might be explored as alternatives that provide a greater degree of precision. Although daily studies have been conducted (e.g. Adimassu et al., 2014; Muluneh et al., 2016; Tilahun, 2006), these have tended to focus on extreme events, whereas our qualitative experience points toward other approaches for analyzing the data.

3.3. Quantitative analysis of rainfall data

In order to focus the analytical approach toward one that addresses the time scales important to farmers, we have first analyzed meteorological station data by month. Furthermore, we have not restricted that analysis to seasons, but include all months, thus shedding light on the important role of months preceding and following the rainy seasons. Multiple temporal scales (monthly, seasonal, annual, and decadal) are also considered to expand the temporal scale options, and give freedom of matching with the temporal scale used by farmers.

Four decades (1970–2009) of monthly rainfall data from one station in southern Ethiopia were analyzed. Monthly rainfall data were acquired from the National Meteorological Agency of Ethiopia for the Wolaita Sodo station, which is the nearest to the communities within which qualitative research took place (Damot Gale District). Statistical methods outlined below were used to analyze the monthly rainfall data obtained from the Wolaita station. Rainfall variability was described using the rainfall variability index, which classifies time-series rainfall into different climatic regime categories (extreme dry, dry, normal and wet classes) relative to the long-term mean, as well as mean, standard deviation and coefficient of variance (ratio of the standard deviation to the mean) values calculated.

The temporal trend (both direction of change and magnitude) of rainfall is tested using Mann-Kendall's tau and Spearman's Rho tests. Statistical significance test ($p < 0.05$) is applied to Spearman's Rho and Mann-Kendall's tau trend tests to detect the level of confidence. In addition to exploring rainfall average amounts and variability, changes in rainfall amount and timing were investigated for monthly, seasonal and annual temporal scales using the percent change in rainfall amount (% deviation). This is calculated as:

$$\text{Rainfall deviation} = (\text{Actual rainfall} - \text{Average rainfall})/\text{Average rainfall} \times 100$$

Finally, a Rainfall Variability Index (δ) for period i is calculated, following Gocic and Trajkovic (2013). This Index is calculated as:

$$\delta_i = (P_i - \mu) / \sigma$$

where P is the rainfall for time period i, and μ and σ are the monthly mean and standard deviation for the period 1970–2009. Rainfall can be classified into extremely dry, dry, normal and wet periods using the categorizations (WMO, 1975) in Table 1.

4. Results

4.1. Farmer perceptions of rainfall

Cochrane (2017b) found farmers from across the three communities in Damot Gale District were adamant that rainfall patterns had changed since the time of their parents and grandparents. However, when

Table 1
Rainfall categorizations where P is the rainfall for time period, and μ and σ are the monthly mean and standard deviation for the period 1970–2009 (WMO, 1975).

Classification	Condition		
Extreme dry	P	$<$	$\mu - 2 \cdot \sigma$
Dry	$\mu - 2 \cdot \sigma$	$< P <$	$\mu - \sigma$
Normal	$\mu - \sigma$	$< P <$	$\mu + \sigma$
Wet	P	$>$	$\mu + \sigma$

describing those changes, smallholder farmers did not use aggregate seasonal or annual rainfall, or even extreme weather events, as their primary metrics, which are commonly used in the academic literature. The changes that smalholder farmers referred to were related to the onset of rainfall, the duration of the rainy seasons, and the end-point of the rain seasons. Qualitative data collected with farmers, through interviews and focus group discussions, outlined that the two rains seasons were not being impacted in the same way, which has implications for studies that assess aggregate annual rainfall. Farmers were operating with different frames of analysis. The metrics smallholder farmers employed had direct implications for them and their livelihoods, such as when clearing and plowing ought to start (which must be done before the onset of rainfall) or what crops they ought to plant (based on required moisture, vulnerability to moisture stresses, and required period to reach maturity). If the onset of rainfall was changing (earlier or later), farmers need to adjust the agricultural activity cycle, or else entire crops may be lost (e.g. clearing and plowing too early may result in reduced soil moisture at the time of planting; clearing and plowing too late may result in a shorter growing period and crops withering before reaching maturity). For farmers, some of the required changes can be made flexibly (e.g. changing the plowing type to allow for row planting for crops that are better suited to that). However, other changes are challenging to adapt to in the short-term. For example, if crop shifting needs to take place, the right type of seed and quantity of that seed needs to be on hand; however, in most cases these seeds are not readily available on the market. As a result, crop shifting requires advance planning.

Based upon qualitative data, many smallholder farmers in the study area believe that rainfall was more consistent in the past, but now it varies from year to year and season to season. For example, an interviewed farmer in a rural area in Damot Gale remarked that the rain “fluctuates from season to season. It is not happening as expected. It is not happening as we experienced in the past.” By ‘fluctuation’, the meaning was that the typical bimodal rainfall patterns were shifting. A male farmer from a focus group discussion stated that the “rain is not coming at the right months and seasons. Planting dates, months and seasons are completely changing.” This comment offered more specific metrics, namely rainfall onset (and related activities that occur before, at, and following the onset of rainfall) and distribution of rainfall during the months. A farmer in his 50s commented that “now it is difficult to predict the right time of rainfall,” while another farmer added that the “crops are drying up because of insufficient rainfall.” The combination of these comments highlights the importance of grappling with these questions – uncertainty has serious consequences, which is particularly acute in areas where food security is prevalent and vulnerability to climate stresses is high (Cochrane and Gecho, 2016). In general, a common experience shared by smallholder farmers, verified in focus group discussions, was that, in the study area of Damot Gale, during the months preceding the ‘short rains’ once had rainfall (starting from January) but now these rains do not begin until March or April. In other words, the onset had been significantly pushed back in the agricultural cycle. These are farmers with decades of experience, and their comments ought to raise concern, as the Government of Ethiopia and the international community attempt to strengthen food security and resilience in these rural areas.

The past, however, was viewed positively, often in a romanticized way. To demonstrate the typical view of the past consider the description of a farmer in her forties, who explained:

> “In the past rain came at the right time. In the past, rain started in January. But, now it has changed completely. It comes at the end of March, even sometimes it delays up to April or May. It does not come at the expected time. It comes outside of the planning time. Most of the time the cropping season it too late. The amount of rainfall has also changed. Sometimes it is insufficient for crops and unevenly distributed. Because of these changes we are not getting a good result from crop production”

Existing data, including those related to extreme drought and famine events, suggest that the regularity of rainfall may not have been as consistent as some perceive. There are many reasons why this perception might have emerged; it could be relative to the time when questions were asked, it could be in relation to the questions and responses regarding shifting patterns, or it might be a selective, potentially romantic, remembering of the past. Yet, others, far fewer in number, say the changes have been occurring throughout their lives. One farmer explained that “I began detecting the changes in rainfall starting from the year of 1984 [Ethiopian Calendar; 1991 Gregorian Calendar].” This happens to be the year the previous government was overthrown, and when the new government took power, and one cannot discount the ways in which minor details such as these allude to politics, particularly in a nation where speaking openly and freely about politics can result in serious negative consequences. The farmer did not explicitly make political references, but the association highlights how changes may be associated with factors beyond rainfall. All data is biased; from the questions posed to the analyses undertaken and the findings presented and interpreted. Analyzing the broader qualitative data provides some insight into the potential biases that are operating, and therefore find avenues to validate and triangulate data. For this study, our objective was not to validate historical perceptions so this was not a critical issue to address. Rather, we sought to gain insight into metrics that were relevant for smallholder farmers. Having those metrics explained by farmers allowed us to pilot new analyses.

One of the complicating challenges when farmers reflect on past yields and rainfall, is that while climate change has taken place, so have many other changes. Amongst these include significant declines in landholding sizes, which negatively affected the traditional farming systems of the area. In addition, the pressure on land and resource (water) use has had implications for livestock, which is critical both as a source of natural fertilizer and as a source of protein in a carbohydrate-based diet (e.g. meat, milk, butter). As population expanded, the lands being utilized also changed, into areas less productive (and more malaria prone), while areas that used to be cultivated on a rotational or multi-cropped basis are being monocropped and overused, negatively affecting soil fertility. While farmers recognize these changes, it is unclear to what extent the challenges are being described (or attributed to) as climate-driven as a result of a line of questioning, or as a result of placing the responsibility of in other realms. In the qualitative data, these narratives emerge—declines of livestock, milk, butter, and land—as do the current changes such as better access to education and healthcare, higher costs for commodities they purchase and, for some, greater food insecurity. The nuance of caution, however, is not teased out in detail. One common cause of change in the study area, which is dominantly Protestant, is that the negative changes of rainfall are divine punishment.

4.2. Quantitative understandings of rainfall

Presentations of long-term rainfall patterns commonly use average annual or seasonal rainfall. In order to explore how different approaches can result in different presentations of data, we first present results of different analytical approaches to the same data. In Fig. 2 we present the data from Wolaita in the form of average monthly rainfall, by decade. The monthly long-term mean rainfall shows that the station receives rainfall throughout the year, with different average amounts in different months. The monthly long-term mean rainfall at Wolaita station ranged from 32 mm on average in December to 207 mm on average in July (see Table 2). The standard deviation of monthly rainfall is highest in August (138 mm) and lowers in January (35 mm). The coefficient of variation (CV) is highest in December (136%) and lowest in May (45%), which is a relatively dry month for the Wolaita station. As presented in the Table 2, the highest percentage variations

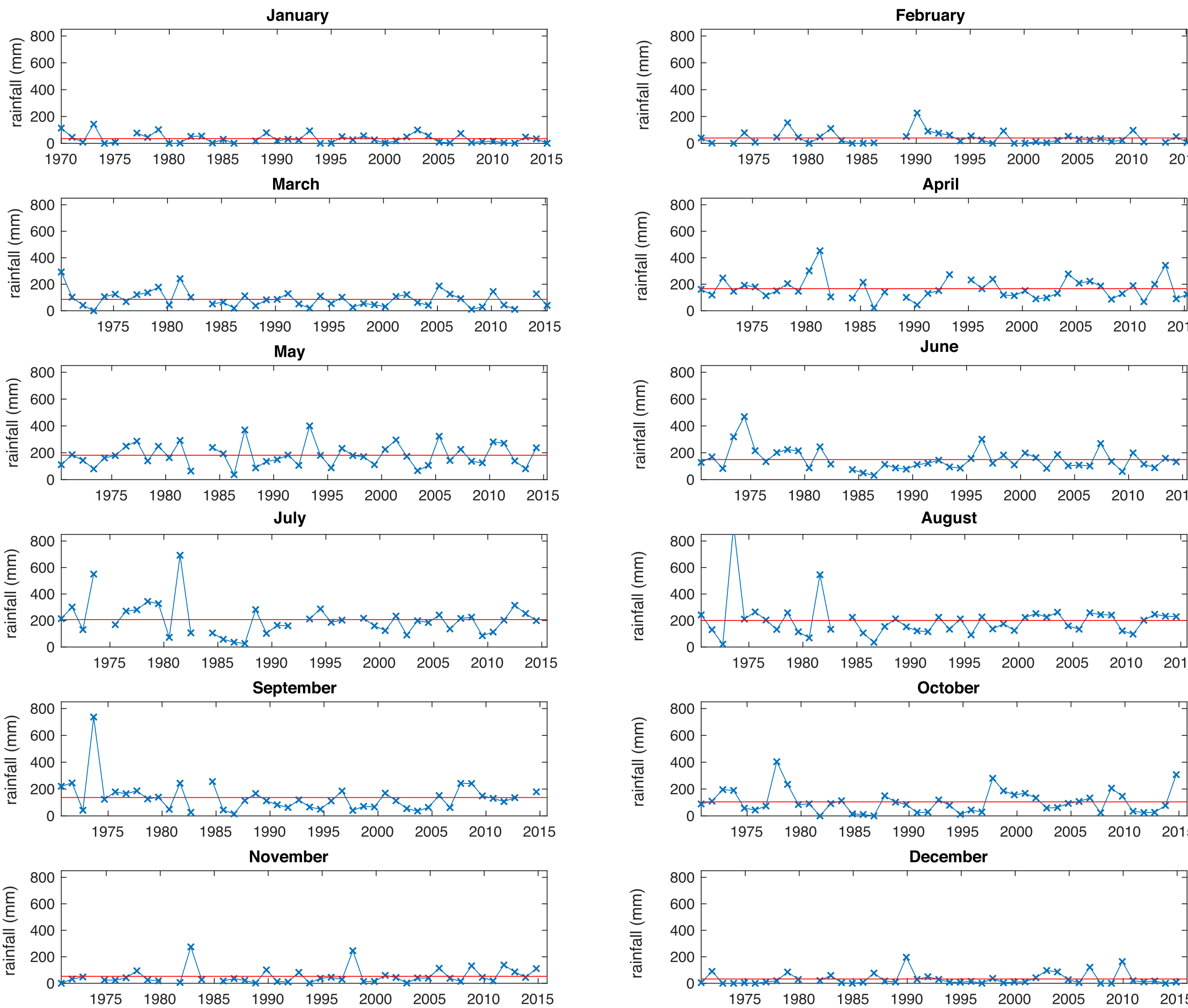

Fig. 2. Average rainfall amount at Wolaita Sodo for each month 1970–2009 (mm) with long-term average value indicated by horizontal red line. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 2
Monthly rainfall climatology.

Monthly rainfall variability				Variability for decadal average of monthly rainfall		
Months	Mean (mm)	Standard deviation (mm)	CV (%)	Mean (mm)	Standard deviation (mm)	CV (%)
January	35.30	35.39	100.25	14.57	37.14	39.23
February	37.98	45.09	118.71	18.84	38.42	49.03
March	86.28	60.17	69.74	21.10	87.22	24.19
April	166.85	81.78	49.01	5.78	165.46	3.50
May	181.03	83.01	45.85	3.70	178.45	2.07
June	148.25	81.17	54.75	48.97	149.40	32.78
July	207.60	122.91	59.20	61.13	206.52	29.60
August	200.16	138.17	69.02	40.38	199.99	20.19
September	137.38	113.02	82.26	56.17	136.82	41.05
October	104.48	86.68	82.96	34.46	105.76	32.58
November	50.85	57.69	113.44	8.62	47.25	18.25
December	32.41	44.38	136.93	16.63	35.06	47.43

occur in months of low rainfall (November, December, January, February).

We next explore a different analytical approach to examining Wolaita rainfall.

What is 'made invisible' in averaging rainfall across the record period (as shown in Table 2) are the variations in monthly rainfall that occur from decade to decade. To demonstrate the extent of that variation, Fig. 3 shows departures from the mean plotted for the same time period for each month. The deviation of monthly rainfall from the mean (in percentage) shows that the highest deviation (495%) occurred in February 1990, while the lowest deficit (100%) occurred in January (1974, 1980 and 1985), February (1971, 1972 and 1973), March (1980 and 1984), November (1970) and December (1972, 2008, and 2013). The percentage deviation of monthly rainfall in general shows greatest apparent variability in November and December. However, when the monthly rainfall is averaged over four decades (1970–2010) to reduce inter-annual variability, the departure from the mean monthly rainfall and variability ranged from 35 mm in December to 206 mm in July, and 2% in May to 49% in February, respectively. The comparison between monthly and decadal averaged monthly rainfall variability shows that the CV of decadal averaged of monthly rainfall is greatly reduced.

We next focus on seasonal and annual rainfall amount (Figs. 4 and

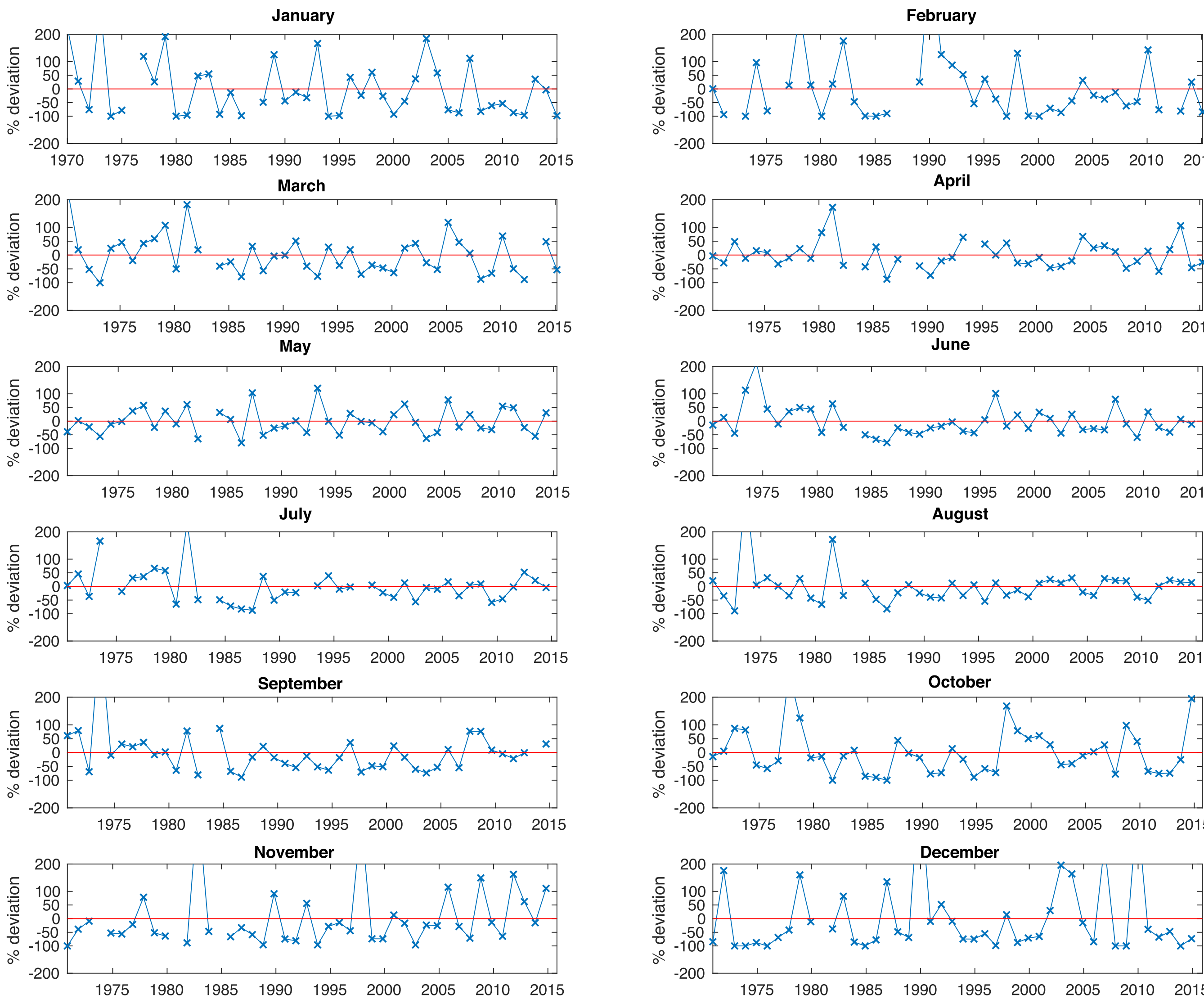

Fig. 3. Rainfall deviation at Wolaita Sodo for each month 1970–2009 (%).

5) and deviations (Figs. 6 and 7) at Wolaita. The highest percentage of deviation in seasonal rainfall was during the *kiremt* season (264%) in 1974, and the lowest was during dry season (−84%) in 1984. The seasonal and annual rainfall variability presented in Table 3 shows that the highest departure from the long-term mean seasonal rainfall, and the largest variability are during *kiremt* (JJAS) (386 mm) and dry season (ONDJF) (CV = 56.5%) respectively. Over the three decades, the annual rainfall has departed largely (459 mm) from the normal annual rainfall with relatively low variability (CV = 33%) compared to the seasonal and monthly rainfall variability observed. The decadal monthly average, which reduces inter-annual variability, presented in Table 4 (below), shows that July and February were months of the highest deviation (206 mm) from the mean and variability (49%). The maximum and minimum percentages deviations in the annual rainfall are 125% and −78% respectively (Fig. 7).

Rainfall trends at Wolaita station were also investigated for various time periods to determine if there has been a decreasing or increasing trend over the period of observation. The results of the trend analysis are summarized in Table 4. For January, March, April, June, July and September, the monthly rainfall trend using Kendall's tau and Spearman's rho showed a decreasing trend with different magnitude, although these trends were not determined to be statistically significant. Increasing trends were found in February, May, August, November and December rainfall, although again these trends were not determined to be statistically significant (at alpha = 0.05). The trend test applied to the decadal average of monthly rainfall shows that February, March, April, June, July, August, and September had a decreasing trend while May, November and December had increasing trend. Trends in decadal average of monthly rainfall were typically weak and statistically insignificant. The temporal trend test applied to the annual rainfall also had a decreasing, though statistically insignificant, trend (Kendall's tau = −0.025 and Spearman rho = −0.09).

We next examine the station data using the Rainfall Variability Index calculated for monthly (Fig. 8) and seasonal (Fig. 9) data. The seasonal rainfall variability index shows that the *kiremt* season was extremely dry in 1986, which preceded a countrywide drought in 1984/85. The dry season, however, was dry and extremely dry in many years (1975, 1981, 1984, 1985, 1986 and 1994). The *belg* season was in wet conditions in 1973 and 1986.

5. Discussions and conclusions

Comparing farmers conversations with quantitative station data, we show that monthly mean rainfall amounts vary throughout the year, with highest rainfall occurring in the main 'rain' seasons of *kiremt* and *belg*. Conversations with smallholder farmers in Wolaita revealed that

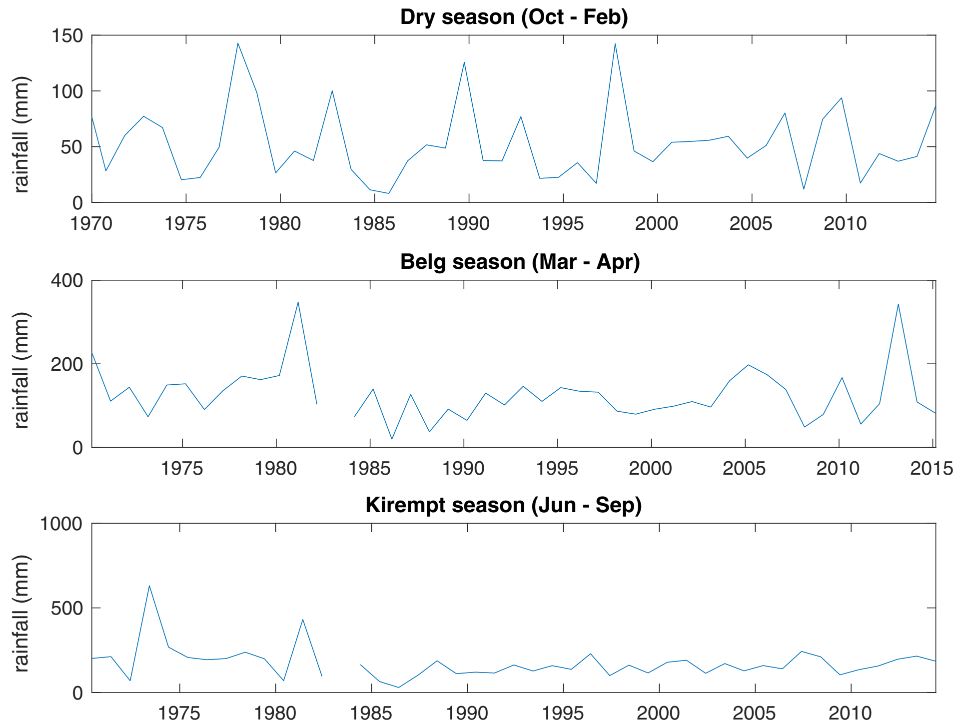

Fig. 4. Seasonal average rainfall amount at Wolaita Sodo for 1970–2009 (mm).

the *belg* season (March–May) is changing in the most impactful ways—not in terms of total rainfall amount but in its timing. In some instances, they explained, the two seasons merge into one long season, with serious impacts on their rain-fed agricultural practice. When rainfall is assessed on a monthly basis, and includes all the months of the year, not just the main rainy seasons (as is commonly done), the data show there is high variability in low rainfall months, which occur in-between the main rainy seasons. This is critical because these minor rainfall events are signals for farmers regarding the initiation of preparatory activities, such as field clearing and plowing. These activities cannot be done too early, or else the soils can harden and this may result in topsoil loss. As a result, farmers await these minor rainfall events in planning the activities that occur before the onset of the main rainy seasons. If these seasons are becoming more variable, as farmers and the data indicate, this presents significant challenges for farmers. These challenges include crop failure resulting from unpredictability in rainfall, where prediction was possible in the past by experienced farmers. It also provides one explanation about why farmers are shifting to short course crops—if their preparatory activities are delayed due to variable rainfall in the months preceding the main rainy season, there will be a shortened growing period, and thus farmers are planting those crops that have the greatest likelihood of full maturation.

In referring to multiple sites in arid and semi-arid regions of Ethiopia, Tilahun (2006) finds that annual variation is primarily a result of changes in the *belg* season. Adimassu, Kessler and Stroosnijder (2014), studying the Central Rift Valley area of Ethiopia, find that there is greatest variability of the *belg* season (March–May), which has also been identified in a number of other studies (Amsalu et al., 2007; Handino, 2014; Meze-Hausken, 2004; Rossell, 2014). Conway (2000) noted that the two rainy seasons were changing in different ways, with the *belg* and *kiremt* being influenced predominantly by either the Indian and Atlantic Oceans, and thus the differences farmers experience in the two seasons aligns with some of the suggested causes of the changes. All of this indicates that the farmers' experiences appear not only related to the Wolaita station, but support broader changes.

Divergence between quantitative analysis and farmers experiences appears in understanding changes in the rainfall through time. The statistical trend test (direction and magnitude) and level of confidence applied to monthly analyses showed a smaller increasing trend in monthly rainfall for February, May, August, October, November and December, while a different magnitude in decadal average monthly rainfall trend analysis was found in May, October, November and December. The annual rainfall also showed a small decreasing trend over time. Importantly, the level of confidence (P-value) calculated for

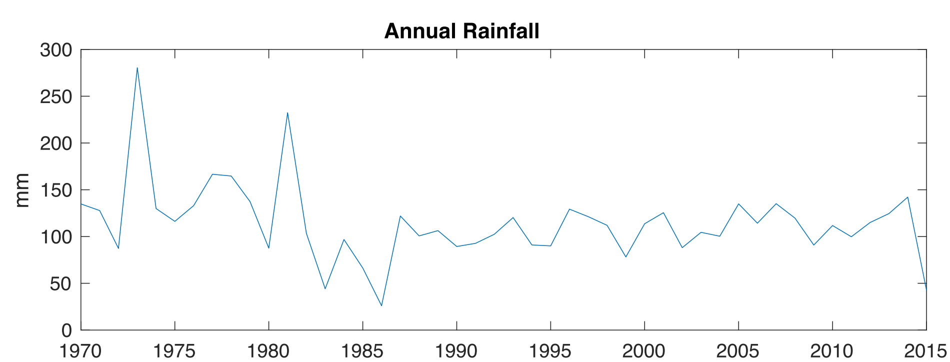

Fig. 5. Annual average rainfall amount at Wolaita Sodo for 1970–2009 (mm).

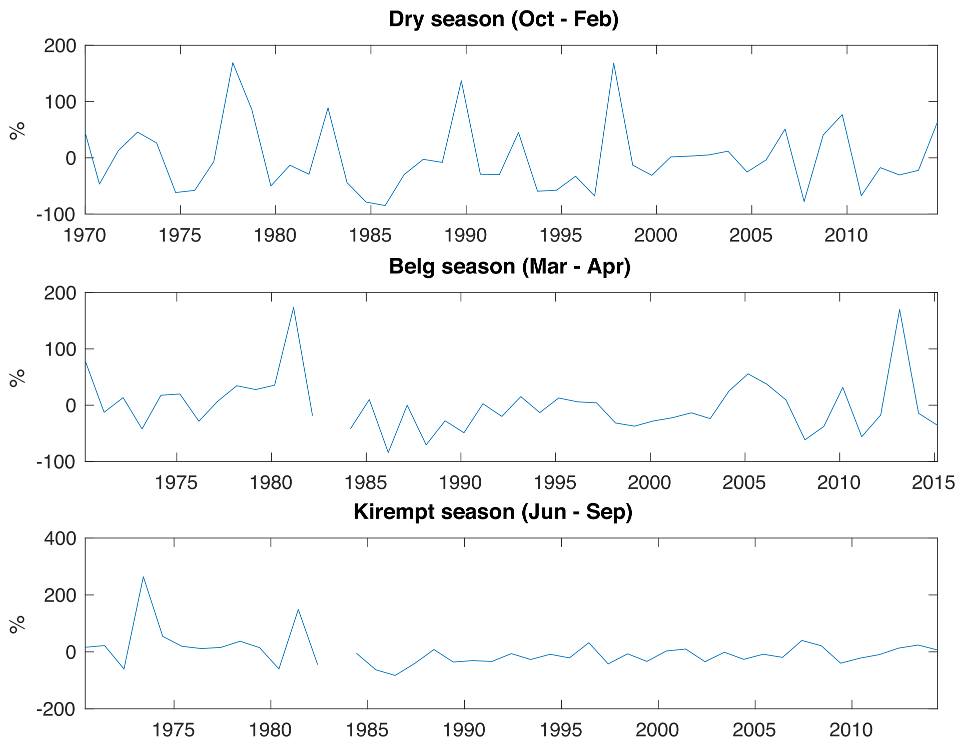

Fig. 6. Rainfall deviation at Wolaita Sodo for each season 1970–2009 (%).

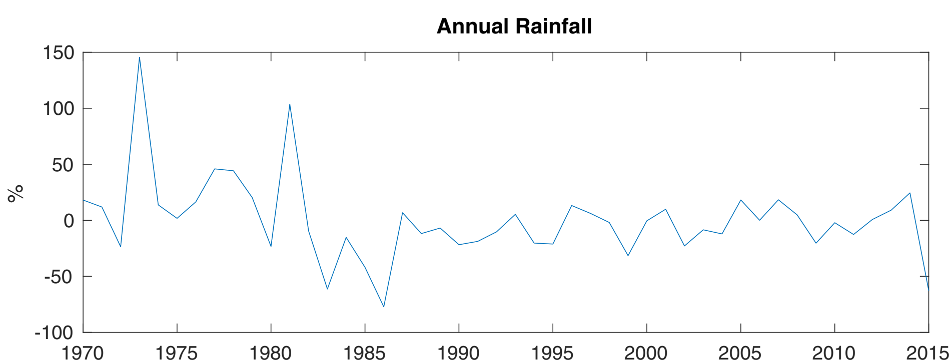

Fig. 7. Rainfall deviation at Wolaita Sodo for annual average 1970–2009 (%).

Table 3
Seasonal and annual climatology.

Months	Mean (mm)	Standard deviation (mm)	CV (%)
Dry season (ONDJF)	261.04	147.63	56.55
Belg season (MAM)	434.17	155.33	35.77
Kiremt season (JJAS)	693.41	386.57	55.74
Annual	1388.62	459.46	33.08

the trend tests were insignificant at alpha = 0.05. If the temporal length of observed data were extended, the analysis conducted may give different results on magnitude of change and the level of confidence for the change, as trends are sensitive to record lengths (Westra et al., 2013). For this region those data are, however, unavailable. Overall, our quantitative results support prior results showing no identifiable rainfall trends (e.g. Bewket and Conway, 2007; Cheung et al., 2008; Conway, 2000; Meze-Hausken, 2004; Tilahun, 2006). In this regard, the Wolaita station does not show that patterns are changing in a uniform way, as farmers have experienced.

For the *kiremt* rainy season months, Handino's (2014) study from southern Ethiopia suggests rainfall variability is decreasing. Handino suggests intra-annual analyses provide additional insight into these trends, both in terms of rainfall amount and variability. In our study, the monthly rainfall variability analysis using CV showed that December and May had the highest and the lowest rainfall variability, respectively. February and May are months in which the decadal average monthly rainfall showed the highest and the lowest CVs. January showed both the highest and the lowest indices when rainfall variability index is used. The highest and the lowest variability indices were captured during the *kiremt* and dry seasons respectively. The years of 1973 and 1986 were years of the highest and the lowest annual rainfall variabilities are captured. In general the years prior to 1982 had high rainfall deviations from the mean. The Rainfall Variability Index provides an alternative way to investigate rainfall changes, variability and characteristics in particular years. The Index calculated for Wolaita shows few recently occurring wet instances of *belg* or *kiremt* rainy seasons in recent years. The scientific analysis diverges somewhat from the experiences and narratives presented by smallholder farmers.

This study sought to complement existing research on rainfall data, and provide new insights regarding differing timescales of rainfall changes and trends. While the literature is inconclusive about trends on annual and seasonal scales (Cheung et al., 2008; Rossell, 2014), this

Table 4
Trend for monthly and decadal average of monthly rainfall.

Monthly rainfall from 1970 to 2009				Decadal average of monthly rainfall		
Months	Kendall's tau	Spearman Rho	P-value	Kendall's tau	Spearman Rho	P-value
January	−0.08	−0.12	0.12	0.00	−0.20	0.45
February	0.01	0.02	0.64	−0.33	−0.40	0.22
March	−0.12	−0.17	0.11	−0.67	−0.80	0.72
April	−0.04	−0.05	0.88	−0.33	−0.40	0.32
May	0.02	0.02	0.71	0.67	0.80	0.56
June	−0.07	−0.12	0.15	−0.33	−0.40	0.32
July	−0.06	−0.13	0.14	−0.33	−0.40	0.53
August	0.11	0.15	0.48	−0.33	−0.40	0.40
September	−0.08	−0.12	0.14	−0.33	−0.40	0.62
October	0.00	−0.02	0.84	0.00	−0.20	0.24
November	0.19	0.31	0.19	0.67	0.80	0.88
December	0.06	0.08	0.59	0.33	0.40	0.40

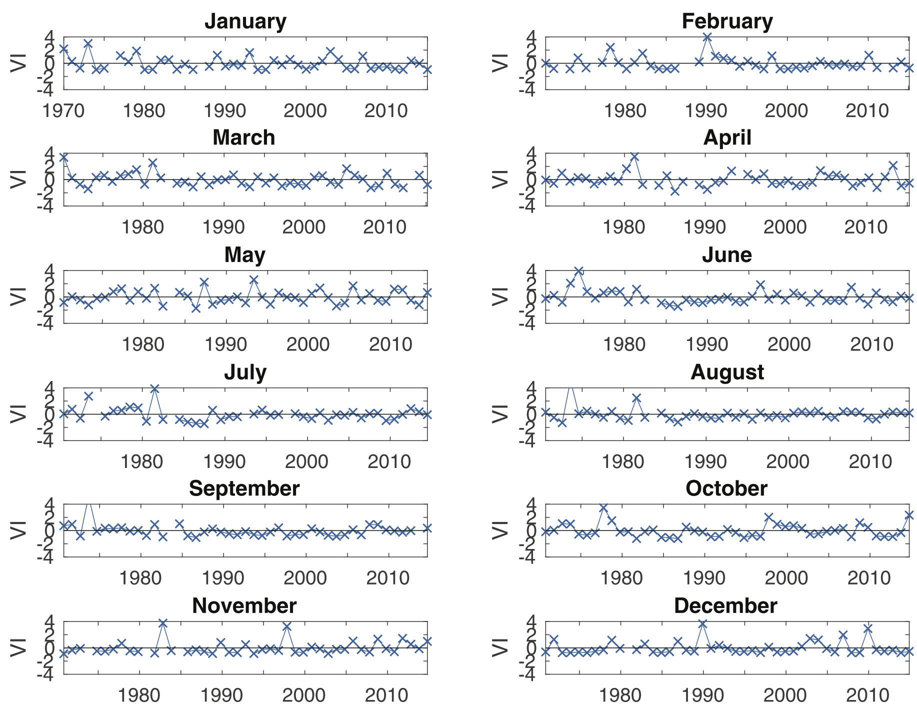

Fig. 8. Rainfall Variability Index (VI) for monthly data.

study used monthly analyses to assess the trends of variability, volume and timing. As with the limitations of aggregating annual and seasonal data, this study also presents limitations, specifically by using a monthly timeframe. Future methodological experimentation is required in order to sufficiently convey the challenges farmers face as lived experiences of variability, in addition to better understanding the trends highlighted within this study. As noted in the methods, other approaches, such as a weekly period for assessment, might allow for greater nuance in trends. Furthermore, specific analysis of the timing of heaviest rainfall events, or shifts in the seasonality of wet and dry seasons may go one step further to understanding farmers lived experiences.

The objective of this paper was to assess the usefulness of a different assessment of meteorological station rainfall data. It was not to (dis) prove a particular narrative. In the process, we have highlighted how the assumptions of researchers may result in analyses and measures that render invisible components of the data that are crucial for farmers. Improving our understanding of localized rainfall trends is essential. As variability increases, it will be increasingly important to convey meteorological information to farmers in ways that are relevant to them and their agricultural livelihoods. Progress is being made in research and practice. For example, a pilot project in India is showing how community specific forecasting and information sharing via communication technologies and public information boards is reducing risks and losses, increasing the ability of farmers to adapt to a changing climate, and increasing yields (Lobo, 2015). The success of this model is not only downscaled data, but we have made progress in finding ways of analyzing and communicating complex data in appropriate and relevant ways for users, by utilizing temporal scales of greater relevance. This paper has shown how existing rainfall data can be analyzed in different ways in order to improve the information that we share with farmers, by changing the way we analyze the data and thereby the insight derived. In presenting the approaches in this paper, we hope to encourage further experimentation with methods and analysis to broaden the types, scales and measures used in assessing rainfall variability.

Funding

S.C.L is funded through the Australian Research Council (DE160100092). Mastawesha Misganaw Engdaw is funded by Austrian Science Fund (FWF) under Research Grant W 1256 (Doctoral Program

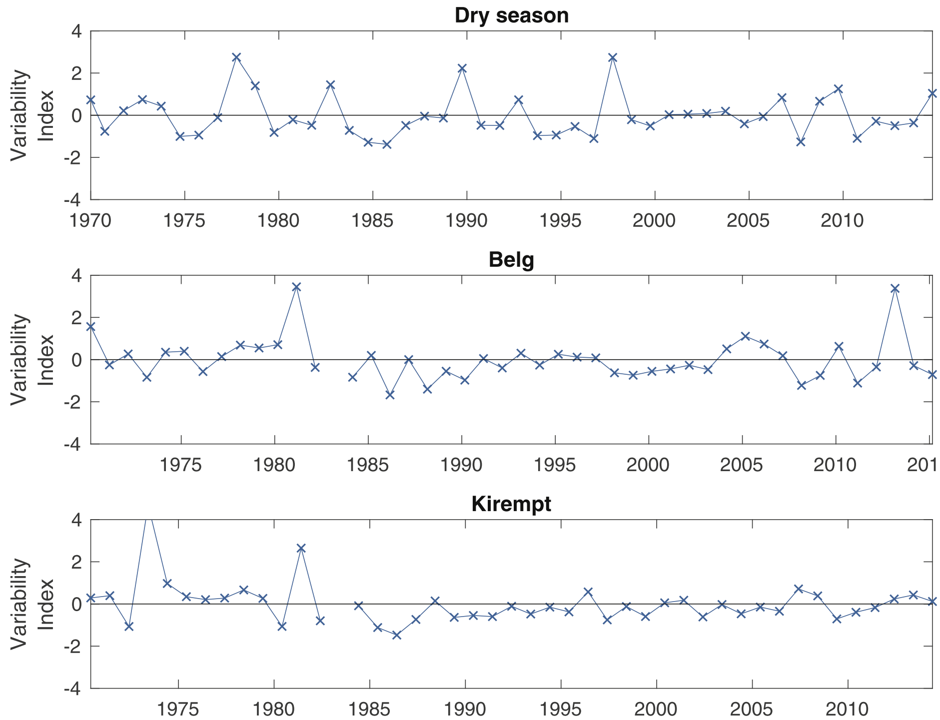

Fig. 9. Rainfall Variability Index for seasonal data.

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Acknowledgements

We thank Jack Moran for his assistance in drafting early versions of the figures.

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