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Comparing observed rainfall variability with small-scale farmers' perceptions: The case of South Wollo, Ethiopia

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Abstract

Perception of environmental change is a prerequisite for adaptation. Thus, it is vital to understand how agricultural communities perceive changing rainfall and how perceived rainfall changes affect their decision-making process. In South Wollo, in the densely populated northern highlands of Ethiopia, small-scale farmers are particularly vulnerable to environmental change. Their livelihoods largely depend on rainfed agriculture which makes them reliant on relatively stable and predictable rainfall conditions. The rainfall regime is characterized by two rainy seasons: the lighter spring rains, locally known as *belg*, and the main rainy season in summer, locally known as *kiremt*.

Six kebeles (smallest administrative unit in Ethiopia) in South Wollo were selected using a purposive sampling approach. A total of 42 semi-structured household interviews and 18 focus group discussions were conducted in the kebeles between November 2017 and February 2018. During the interviews, information was gathered on the socio-economic composition of the household, main activities, land and crop management practices as well as perceived changes of rainfall and land degradation, the impacts of these changes and the respondents' strategies to address them. The kebeles were grouped according to the rainy season the farmers use for cropping: only belg, only kiremt or both seasons. Changing rainfall perceptions were analyzed with regard to what had changed, how it had changed and how it impacted the farmers' daily lives and agricultural activities. An analysis of rainfall trends and rainfall variability in the kebeles was performed using daily precipitation estimates from the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) between 1981 and 2017. Rainfall was analyzed regarding drought years, rainfall amount, number of rainy days, timing of the rainy seasons, rainfall intensity and frequency and intensity of extreme events. The coefficient of variation (CV) was used to assess variability and the non-parametric Mann-Kendall trend test and Sen's slope estimator were used to analyze direction and magnitude of trends.

Respondents perceived decreasing rainfall amounts and a later and increasingly unpredictable onset of belg rains. Perceived changes in kiremt were mainly associated with timing, in particular an earlier cessation of the rainy season, and decreasing amounts of rainfall. Regarding changes in extreme events and rainfall intensity, respondents gave mixed answers. Dry spells were hardly mentioned. Analysis of the meteorological data showed a statistically significant ($p \leq 0.05$) decreasing trend for rainfall amount and an increasingly late onset of belg. The duration of belg and the total dry spell length became more variable. For kiremt, increasing trends in the amount of rainfall were found in one kebele group and an increasing number of rainy days and a decreasing frequency of very wet days in another. The intensity and frequency of extreme events during kiremt has become more variable. Overall, respondents cropping during belg had perceived changes in rainfall in accordance with the change in meteorological

data. Farmers cropping during kiremt had a more negative, sometimes even contradictory perception of the changes in rainfall than the precipitation data showed.

Farmers primary metrics in assessing rainfall are onset, cessation and duration of the season(s). The availability of a consistent time series with high spatial and temporal resolution in CHIRPS made a detailed assessment of these aspects possible. Not only the amount of rainfall matters, but also the distribution of rainfall throughout the season. Farmers perceive rainfall in terms of how it affects their agricultural activities. Crop failure may be attributed to changing rainfall even though other aspects such as land degradation or declining soil fertility This can lead a perception of rainfall decline, even though other aspects may be more important drivers.

Table of contents

A List Of Figures **5**

B List Of Tables **5**

C List Of Abbreviations **7**

1 Introduction **9**

1.1 BACKGROUND 9
1.2 LITERATURE REVIEW 10
1.2.1 Perceptions of Environmental Change 10
1.2.2 Meteorological Trends and Variability of Rainfall in the Ethiopian Highlands 13
1.3 RESEARCH OBJECTIVES 15

2 Study Area **15**

3 Data **19**

3.1 RESEARCH SITE SELECTION 19
3.2 QUALITATIVE INTERVIEWS 20
3.3 RAINFALL ESTIMATES 21

4 Methods **24**

4.1 RAINFALL ANALYSIS 24
4.1.1 Rainy Seasons 25
4.1.2 Total Rainfall and Rainy Days 26
4.1.3 Timing of the Rainy Seasons 26
4.1.4 Dry Spells 29
4.1.5 Intensity and Extreme Events 29
4.1.6 Mann-Kendall Trend Test and Sen's Slope Estimator 31
4.2 INTERVIEW ANALYSIS 33

5 Results **34**

5.1 RAINFALL ANALYSIS 34
5.1.1 Annual Indices 34
5.1.2 Standardized Rainfall Anomaly 36
5.1.3 Seasonal Total Rainfall and Rainy Days 38
5.1.4 Timing of the Rainy Seasons 40
5.1.5 Dry Spells 45
5.1.6 Intensity and Extreme Events 46
5.2 INTERVIEW ANALYSIS 50

5.2.1 Belg Only Kebele 50
5.2.2 Belg and Kiremt Kebeles 51
5.2.3 Kiremt Only Kebeles 52
5.2.4 Beyond Rainfall 52
5.2.5 Causes 53

6 Discussion 53

7 Conclusions 62

D References 63

Annex 73

A List of figures

Figure 1 Maps of the location of South Wollo in Amhara Regional State in Ethiopia and of the location of the study kebeles within South Wollo with elevation 16

Figure 2 Map of the study area and CHIRPS precipitation estimates with example days for high precipitation during belg and kiremt 17

Figure 3 Rainfall regime in the study area. 10-day rolling mean of the mean daily precipitation in the six study kebeles between 1981 and 2017 18

Figure 4 Photograph of the landscape in South Wollo with gully erosion. Photo credit: Juliane Groth 19

Figure 5 Photograph of the data collection showing a focus group discussion with village mapping. Photo credit: Juliane Groth 20

Figure 6 Overview of the CHIRPS calculation process 22

Figure 7 Daily Precipitation and cumulative precipitation anomaly for one year including long-term annual mean, long-term window mean and respective cumulative anomalies, onsets for threshold, yearly and window methods 28

Figure 8 Flow chart for organizing and categorizing perceptions of rainfall changes from interview data including example quotes 33

Figure 9 Seasonal results for standardized rainfall anomaly for all kebele groups and rainy seasons 37

Figure 10 Onset and cessation of belg with standard deviations in four timesteps for the kebeles where belg is used for cropping 41

Figure 11 Onset and cessation of kiremt with standard deviations in four timesteps for the kebeles where kiremt is used for cropping 44

Figure 12 Mean seasonal and annual rainfall and its coefficient of variation (CV) in the study area between 1981 and 2017 54

Figure 13 Belg season in a wet and a dry example year in the kebele using only belg for cropping 56

Figure 14 Summary of the results 57

Figure 15 All indices where coefficient of variation (CV) has increased at least since the 1990s for each kebele group. 58

B List of tables

Table 1 Details of the study kebeles as described by local officials 19
Table 2 Summary of the rainfall indices used in the analysis 24
Table 3 SRA classification 30
Table 4 Results for indices calculated at the annual level for the three groups of kebeles 35
Table 5 Mean percentage of total annual rainfall (1981-2017) each season receives per kebele group 35
Table 6 Results of the Mann-Kendall trend test and Sen's slope estimator for the indices calculated at the annual level for the three groups of kebeles 36
Table 7 Results for total rainfall and rainy days during belg for the kebele groups using belg for cropping 38
Table 8 Results of the Mann-Kendall trend test and Sen's slope estimator for total rainfall and rainy days during belg for the two kebele groups using belg for cropping 39
Table 9 Results for total rainfall and rainy days during kiremt for the kebele groups using kiremt for cropping 39
Table 10 Results of the Mann-Kendall trend test and Sen's slope estimator for total rainfall and rainy days during kiremt for the two kebele groups using kiremt for cropping 40
Table 11 Results for the timing indices during belg for the kebele groups using belg for cropping 42
Table 12 Results of the Mann-Kendall trend test and Sen's slope estimator for the timing indices during belg for the two kebele groups using belg for cropping 42
Table 13 Results for the extreme events and intensity indices during kiremt for the kebele groups using kiremt for cropping 48
Table 14 Results of the Mann-Kendall trend test and Sen's slope estimator for the extreme events and intensity indices during kiremt for the two kebele groups using kiremt for cropping 49

C List of Abbreviations

ARC2	African Rainfall Climatology version 2
avgdsl	average dry spell length
BK	kebeles using belg and kiremt for cropping
BO	kebeles using only belg for cropping
CCI	Commission for Climatology
CDD	maximum number of consecutive dry days
CHIRP	Climate Hazards Group Infrared Precipitation
CHIRPS	Climate Hazards Group Infrared Precipitation with Stations
CHPclim	Climate Hazards Group Precipitation Climatology
CLIVAR	Climate Research Programme project for Climate Variability and Predictability
CMORPH	Climate Prediction Center morphing method
CPC TIR	NOAA Climate Prediction Center Dataset
CV	coefficient of variation
dur	duration of the rainy season
ENSO	El Niño – Southern Oscillation
ETCCDI	Expert Team on Climate Change Detection and Indices
FTP	file transfer protocol
GCOS	Global Climate Observing System
GriSat	Globally Gridded Satellite
IPCC	Intergovernmental Panel on Climate Change
ITCZ	Intertropical Convergence Zone
KO	kebeles using only kiremt for cropping
LST	Land Surface Temperature
MK test	Mann-Kendall trend test
MODIS	Moderate Resolution Imaging Spectrometers
NOAA	National Oceanic and Atmospheric Administration
PERSIANN	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks
R95p	very wet days
R99p	extremely wet days
rd	number of rainy days
RR	total rainfall

Rx1day	maximum 1-day precipitation
SDII	Simple Daily Intensity Index
SRA	standardized rainfall anomaly
TAMSAT	Tropical Applications of Meteorology using Satellite Data
TARCAT	African Rainfall Climatology and Time-series
TIR	thermal infrared
totdsl	total dry spell length
TRMM	Tropical Rainfall Measuring Mission
USGS	United States Geological Survey
WMO	World Meteorological Organization

1 Introduction

1.1 Background

Since the 1950s, climatic conditions across the earth have been changing at an unprecedented speed. On a global scale, the atmosphere and the ocean have warmed, snow, ice and glaciers have melted and sea levels have risen with severe impacts on natural and human systems (IPCC 2015). In Sub-Saharan Africa, agriculture is largely rainfed and at the same time, the agricultural sector makes up a substantial share of the overall economy. On the one hand, this makes farmers particularly vulnerable to changes in climate. On the other hand, it puts them in a unique position when it comes to observing these changes (Ayanlade et al. 2017; Simelton et al. 2013). Since the impacts of changing rainfall, i.e. potential crop loss, are also influenced by infrastructural, institutional and technological development as well as poverty, it can result in intense pressure on small-scale farmers' livelihoods (Osbahr et al. 2011; Rockström et al. 2010; Simelton et al. 2013).

In Ethiopia, the national economy is particularly sensitive to changes in climate due to its high dependency on agriculture (Bryan et al. 2009; Simane et al. 2016). Agriculture, forestry and fishing contribute more than 32% to the Ethiopian gross domestic product (FAO 2020). Livelihoods largely depend on rainfed agriculture and chronic food insecurity affects 10% of the population, which means these households' food supply cannot meet their needs, even in years with average rainfall and they are dependent on food aid (Conway and Schipper 2011). In the mountainous terrain in the highlands of Ethiopia, climate conditions and the sensitivity of the local population to climate variability can change within just a few kilometers (Simane et al. 2016). An improved understanding of how changing climate conditions are perceived by agriculture-dependent small-scale farmers is important in the development of policies and programs to promote adaptation of the agricultural sector (Bryan et al. 2009).

Perceptions of environmental change are considered a prerequisite for adaptation. Adaptation means the "process of adjustment to actual or expected climate and its effects" (IPCC 2015). It depends on whether the impacts of change are perceived as a risk and whether it should (and could) be acted upon (Adger et al. 2009; Alessa et al. 2008). The extent to which environmental change is perceived locally shapes vulnerability: the level of and support for adaptation can vastly alter the impacts of change (Fosu-Mensah et al. 2012; Howe et al. 2014). How people think about and perceive environmental change is not necessarily accurate or complete. An increasing divide between actual change and perceived change can lead to an underestimation of climate risks and a lack of adaptation or maladaptation, which can result in severe consequences, especially in regions where much of the population is highly exposed (Alessa et al. 2008; Howe et al. 2014; Idrissou et al. 2020; Kosmowski et al. 2016).

Small-scale farmers are not only exposed to variable climate conditions, they also observe them actively (Ayal and Leal Filho 2017). In fact, agriculture-dependent communities in rural areas were found to have a higher level of awareness of locally changing climate conditions (Howe et al. 2014; Kosmowski et al. 2016). Farmers draw on personal experience to process environmental change and they make analytical statements, e.g. by discussing the merit of different adaptation strategies when communicating about climatic conditions (Marx et al. 2007). They perceive change not necessarily in meteorological terms but rather as it affects their agricultural activities. Thus, perceptions are not necessarily determined by long-term changes of measurable climate parameters such as rainfall (Bryan et al. 2009; Kosmowski et al. 2016). Some climate parameters may be easier to observe by small-scale farmers than others and meteorological data and individual perceptions may measure fundamentally different constructs. While meteorological data represents people's exposure to climate change, perceptions are linked to experienced climate impacts and adaptive capacity. Distinguishing between exposure, impacts and the farming system's sensitivity to rainfall is crucial (De Longueville et al. 2020; Dickinson et al. 2017; Leclerc et al. 2013; Simelton et al. 2013).

Both sources, meteorological data and perceptions of local communities, should be used in a complementary way rather than assessing which is more "accurate". Developing solutions for climate variability, climate change and its impacts on small-scale farmers' livelihoods through the integration of different knowledge sources can prove to be more beneficial than relying exclusively on meteorologically observed changes in climate (Dickinson et al. 2017; Mekonnen et al. 2018). After all, regardless of whether the two sources produce concordant results, the actions small-scale farmers take in response to the changes they perceive and their consequences are real (Meze-Hausken 2004).

1.2 Literature review

1.2.1 Perceptions of environmental change

Most studies on African small-scale farmers' perceptions of environmental change in general and rainfall change in particular conclude that the farmers feel their lives are becoming increasingly challenging. In Ethiopia, a majority of farmers were found to perceive a decline in the amounts of annual and/or seasonal rainfall (Bryan et al. 2009; Esayas et al. 2019). In studies where perceptions of rainfall changes were assessed in more detail, farmers usually report increasingly erratic and unpredictable rainfall, with a later onset and an earlier cessation of the rainy season(s), increasing rainfall intensity and an increasing occurrence of untimely rainfall and drought frequency (Asfaw et al. 2018; Ayal and Leal Filho 2017; Habtemariam et al. 2016; Mekonnen et al. 2018; Wagesho and Yohannes 2016). According to the farmers, rainfall in the Ethiopian highlands appears to be merging from two distinct into one long season

(Cochrane et al. 2020; Meze-Hausken 2004). Farmers in the higher altitude areas seem to be more affected than those in the lowlands (Deressa et al. 2011). Temperatures are reported to be increasing (Asfaw et al. 2018; Mekonnen et al. 2018). Elsewhere in sub-Saharan Africa, changes in the timing and predictability of rainfall are among the most perceived phenomena as well (Ayanlade et al. 2017; De Longueville et al. 2020; Dickinson et al. 2017; Idrissou et al. 2020; Kosmowski et al. 2016; Mkonda and He 2017; Ogalleh et al. 2012; Simelton et al. 2013). Higher rainfall variability and higher rainfall intensity, i.e. wet seasons becoming wetter and dry seasons becoming drier, have also been perceived (Fosu-Mensah et al. 2012; Salerno et al. 2019). Whether or not these perceptions are concordant with meteorological data differs between study regions, data sources, data quality and time frames. Madhuri and Sharma (2020) found in a systematic literature review on perceptions of climate change, that farmers perceived changes in temperature are mostly in agreement with meteorological evidence, while changes in precipitation were aligned with meteorological evidence in 43 out of 70 studies.

The most influential factors in climate and rainfall change perceptions were found to be access to information on climate, access to extension services, education, farm location and distance to markets, income and farming experience (Ayanlade et al. 2017; Bryan et al. 2009; Debela et al. 2015; Deressa et al. 2011; Esayas et al. 2019; Fosu-Mensah et al. 2012; Habtemariam et al. 2016; Mainardi 2018; Tesfahunegn et al. 2016). Perceived causes for changing rainfall, if farmers were able to name them, were often identified as deforestation or deistic causes (Ayal and Leal Filho 2017; Habtemariam et al. 2016; Mekonnen et al. 2018). The impacts of perceived rainfall changes are in many cases reported to be severe. Farmers are increasingly confused about planting dates which results in a reduction in crop yield (Asfaw et al. 2018). Also, farmers perceive a decline in crop productivity as a result of declining rainfall (Adimassu et al. 2014; Adimassu and Kessler 2016). Especially in areas where food insecurity is prevalent and vulnerability to climate stress is high, the negative impact of climate and rainfall change on agriculture is considered a salient risk to farmers' livelihoods and economic development (Cochrane et al. 2020; Debela et al. 2015).

Possible discrepancies between perceived and observed environmental change can be interpreted in multiple ways. Some studies argue that while rainfall may not have changed significantly, the need for and availability of water have. An expansion of the agricultural area into marginal lands to produce more crops for a growing population has become common. In addition to a reduction in fallow, this has led to increased land degradation, soil erosion and lower moisture availability for plant growth and thus reduced productivity (Adimassu et al. 2014; Deressa et al. 2011; Meshesha et al. 2012; Meze-Hausken 2004). Higher temperatures and higher evapotranspiration may further exacerbate water stress and lead to perceived changes in rainfall (Mekonnen et al. 2018; Osbahr et al. 2011). As these factors may result in crop failure, it is likely that farmers perceive agronomic drought rather than meteorological drought. To meet the needs of local farmers' livelihoods, e.g. crop and pasture growth, rainfall must be sufficient in amount and distribution over time. In case of a negative rainfall anomaly, the gap between rainfall demand and supply widens (Meze-Hausken 2004; Slegers and Stroosnijder 2008). Also, perception of changing rainfall is dependent on the crops farmers grow. While increasing yields were perceived to be the result of improved technologies or better crop varieties, decreasing yields were perceived to be caused by changing climate and rainfall (Habtemariam et al. 2016).

Smallholders' perceptions were found to be driven by changes in rainfall duration and distribution rather than quantity, e.g. more erratic or unpredictable rainfall refers to changes in the timing of the rainy season (Below et al. 2015; Fosu-Mensah et al. 2012; Roncoli et al. 2002; Simelton et al. 2013). Cochrane et al. (2020) highlighted that farmers do not use aggregate rainfall or extreme events as their primary metrics, they refer to onset, duration and cessation of the rainy seasons instead. In particular in an area where two rainy seasons are perceived separately, rainfall is considered based on the agricultural activity calendar. Local farmers are more likely to perceive agricultural drought than meteorological drought, i.e. there is a need for the optimal amount of rainfall at the right time and minor differences within a season can have a major influence on whether or not it is possible to harvest (Ayal and Leal Filho 2017; Mekonnen et al. 2018; Rosell and Holmer 2007). The perception of climate change and variability is thus expressed in light of the effects on the farmers' livelihoods (Ogalleh et al. 2012).

Also, perceptions are modified by experiential factors. A farmer's decision-making process is influenced by recent events which may drive a belief that climate has changed (Bryan et al. 2009; Debela et al. 2015; Mertz et al. 2009; Simelton et al. 2013). This can also include the weather during the data collection period (Habtemariam et al. 2016). Vivid memories of extreme weather events such as severe drought or flooding may also influence perceptions of changing rainfall (De Longueville et al. 2020; Howe et al. 2014; Marx et al. 2007; Simelton et al. 2013).

There are shortcomings of different data sources when assessing rainfall change and variability as well as perceptions. Using rainfall data from gauge stations is problematic since they rarely offer long-term consistent timeseries. Also, especially in areas where spatial variability of rainfall is high and gauge stations are rare, using the data from a station that is not at the location where the perception data is acquired can cause errors (Adimassu et al. 2014; De Longueville et al. 2020; Dickinson et al. 2017; Meze-Hausken 2004). Satellite-based rainfall estimates can alleviate some of these problems, depending on spatial and temporal resolution.

A strong focus of extension workers, institutions and non-governmental organizations on changing rainfall patterns, climate change and drought may also manifest narratives of change. Media stories focused on negative developments further reinforce this development (Below et al. 2015; De Longueville et al. 2020; Mertz et al. 2009; Meze-Hausken 2004). Processes of identification and affiliation relying on culture, values and beliefs influence the way people perceive and talk about climate-related problems. Cognitive limitations can cause a distortion of farmers' memories of how rainfall used to be. Through wishful thinking consistent with decision goals, personality characteristics and preexisting beliefs, their responses in an interview situation may be different (Bryan et al. 2009; Hansen et al. 2004; Scoville-Simonds 2018). Respondents might also be inclined to paint a negative picture of their situation in order to attract funding (De Longueville et al. 2020; Nielsen et al. 2012).

Attention to the sociolinguistics can enrich data collection by highlighting cultural meanings and power differentials in public discourse. Obtaining interview data from local farmers in a language the researcher is not familiar with comes with the risk that nuances may get lost in translation (Roncoli 2006; Simelton et al. 2013). The way questions are posed while obtaining the data can alter the results as for example unprompted questions result in respondents sharing the information they find the most salient or relevant whereas specific questions can facilitate comparison with meteorological data (Dickinson et al. 2017). Since climate reference scales are not homogenous, attributes not captured in the dataset might shape perceptions. Climate is perceived as an interconnected system and perception of change in one indicator may be linked to those in others (Debela et al. 2015; Howe et al. 2014; Mainardi 2018).

1.2.2 Meteorological trends and variability of rainfall in the Ethiopian highlands

Rainfall in the highlands of Ethiopia has been studied intensively, however, when comparing the literature on the topic, the results seem conflicting. Differences in methodology and data lead to sometimes vastly different results. The studied timeframe, whether station- or satellite-based data is used, whether data is missing, the exact study area and the temporal resolution of the data can influence whether changes in rainfall are determined or not. For example, in the 1980s, the region was affected by multiple severe droughts (Ayalew et al. 2012; Seleshi and Zanke 2004; Suryabhagavan 2017; Viste et al. 2013). In the 1990s however, the region received abundant rainfall in parts of the highlands, which means the choice of the timeframe can obscure trends (Bewket and Conway 2007).

Seleshi and Demaree (1995) found a decline in mean monthly rainfall in the north central highlands between 1945 and 1984 mainly explained by reduced rainfall in July and August. Similarly, Mekonen and Berlie (2020) report a decline in annual and decadal rainfall since 1900 with an abrupt decline since the 1970s. Decreasing annual rainfall was also found by Asfaw et al. (2018) and Addisu et al. (2015). Since rainfall in the highlands knows two rainy seasons, the main rainy season (kiremt) in summer and the lighter spring rainy season (belg), rainfall is most often analyzed at the seasonal scale. For the amount of rain during kiremt, decreasing trends were found by Asfaw et al. (2018) in the 1901-2014 period. Others found increasing trends for kiremt in their respective study area, although these trends were not statistically significant everywhere (Alemayehu and Bewket 2017; Bewket and Conway 2007; Mekonen and Berlie 2020; Mohammed et al. 2018; Rosell 2011; Rosell and Holmer 2007; Seleshi and Zanke 2004). Trends in the amount of belg rainfall are mostly described as decreasing (Alemayehu and Bewket 2017; Asfaw et al. 2018; Mekonen and Berlie 2020; Rosell 2011; Rosell and Holmer 2007). No trends in rainfall amounts or non-significant changes were also found by a number of studies (Alemu and Bawoke 2019; Ayalew et al. 2012; Conway 2000; Gebrechorkos et al. 2019a, 2019b; Mengistu et al. 2014; Seleshi and Camberlin 2006; Suryabhagavan 2017; Viste et al. 2013; Weldegerima et al. 2018).

Some studies looked beyond just rainfall amounts and analyzed changes in extreme events or dry spells. Asfaw et al. (2018) describe an increasing number of drought years. Gebrechorkos et al. (2019a) found decreasing intensity of extreme events while Bewket and Conway (2007) noted an increase in heavy rain in the city of Dessie and a decrease in other parts of Amhara. A decrease in length of the longest annual dry spell and an increase in the longest wet spell in parts of South Wollo was found by Mohammed et al. (2018) and Gebrechorkos et al. (2019a) noted a decrease in wet spell length. No trends for dry spells, rainfall intensity and the frequency of extreme events were found by Gebrechorkos et al. (2019a) and Seleshi and Camberlin (2006). Overall, no systematic patterns in trends and spatial variations of extreme rains were found in the north central highlands. Patterns were mixed with only few significant trends (Mohammed et al. 2018). The timing of the rainy seasons was the subject of only few studies. A later start of belg and an earlier start of kiremt was noted by Rosell (2011). Rosell and Holmer (2007) mention shorter rainy seasons and Ayalew et al. (2012) found an earlier cessation of kiremt rains to affect the growing season. A shift of the rainfall regime from monomodal to bimodal is noted by some authors (Mohammed et al. 2018; Rosell 2011).

Temporal variability of rainfall was found to have increased in the study area by Rosell and Holmer (2007) while Abtew et al. (2009) describe the temporal variation in the study area as largely stable. In general, it is noted that rainfall in the highlands is highly variable, with the lighter belg rains showing greater variability than the rains during kiremt or annual rainfall (Alemu and Bawoke 2019; Mekonen and Berlie 2020; Mohammed et al. 2018; Rosell 2011; Weldegerima et al. 2018). Complex patterns of rainfall and high spatial variability at a subregional scale are consistently found (Abtew et al. 2009; Addisu et al. 2015; Alemu and Bawoke 2019; Bewket and Conway 2007; Mohammed et al. 2018). The literature on rainfall change and rainfall variability shows an overall inconclusive picture. The highly localized patterns in the study area indicate the need for local rainfall analysis when comparing the meteorological data with small-scale farmers' perceptions.

1.3 Research objectives

Due to the high spatial variability of rainfall in the Ethiopian highlands, a localized assessment of rainfall change is advisable. As mentioned, rainfall data from gauge stations is neither available locally in the villages where the interview data was collected, nor in a consistent timeseries over long periods. The Climate Hazards Group Precipitation with Stations (CHIRPS) dataset provides the opportunity to assess rainfall changes and rainfall variability locally at a high spatial (0.05°) and temporal resolution (daily) (Funk et al. 2015a). The first research objective is thus providing a detailed analysis of trends and variability in rainfall in South Wollo since 1981. Variability includes "variations in the mean state and other statistics (such as standard deviations, the occurrence of extremes, etc.) of the climate on all spatial and temporal scales beyond that of individual weather events" (IPCC 2015).

Local perceptions of environmental change were assessed through qualitative semi-structured household interviews and focus group discussions. The literature mentions small-scale farmers perceiving changes in rainfall through the timing and duration of rain rather than aggregate amounts. The study aims to analyze how rainfall is perceived to be changing by small-scale farmers in South Wollo, which aspects of the rain are changing and how it impacts the farmers' livelihoods. Asking unprompted questions about rainfall in semi-structured interviews can improve the understanding on the aspects of rainfall that are most relevant to local farmers. Considering the rainfall regime is bimodal, it will be assessed whether one rainy season is more affected than the other and how changes in the different seasons are perceived.

Lastly, the study aims to contribute to the literature on perceptions of environmental change by focusing on aspects such as timing, duration and extreme events. CHIRPS offers the opportunity to better capture these particular aspects of rainfall through its high temporal and spatial resolution and the availability of a consistent timeseries than for example station data. No studies so far have used CHIRPS to assess rainfall changes and perceptions of local smallholders.

2 Study area

Ethiopia is a landlocked country in the Horn of Africa, bordered by Djibouti and Eritrea to the North, Somalia to the East, Kenya to the South and Sudan and South Sudan to the West. It is the second most populous country in Africa, characterized by rapid population growth with approximately 106.4 million inhabitants in 2017 compared to only 36 million in 1981 (World Bank 2020). The study was conducted in six kebeles, the smallest administrative unit in

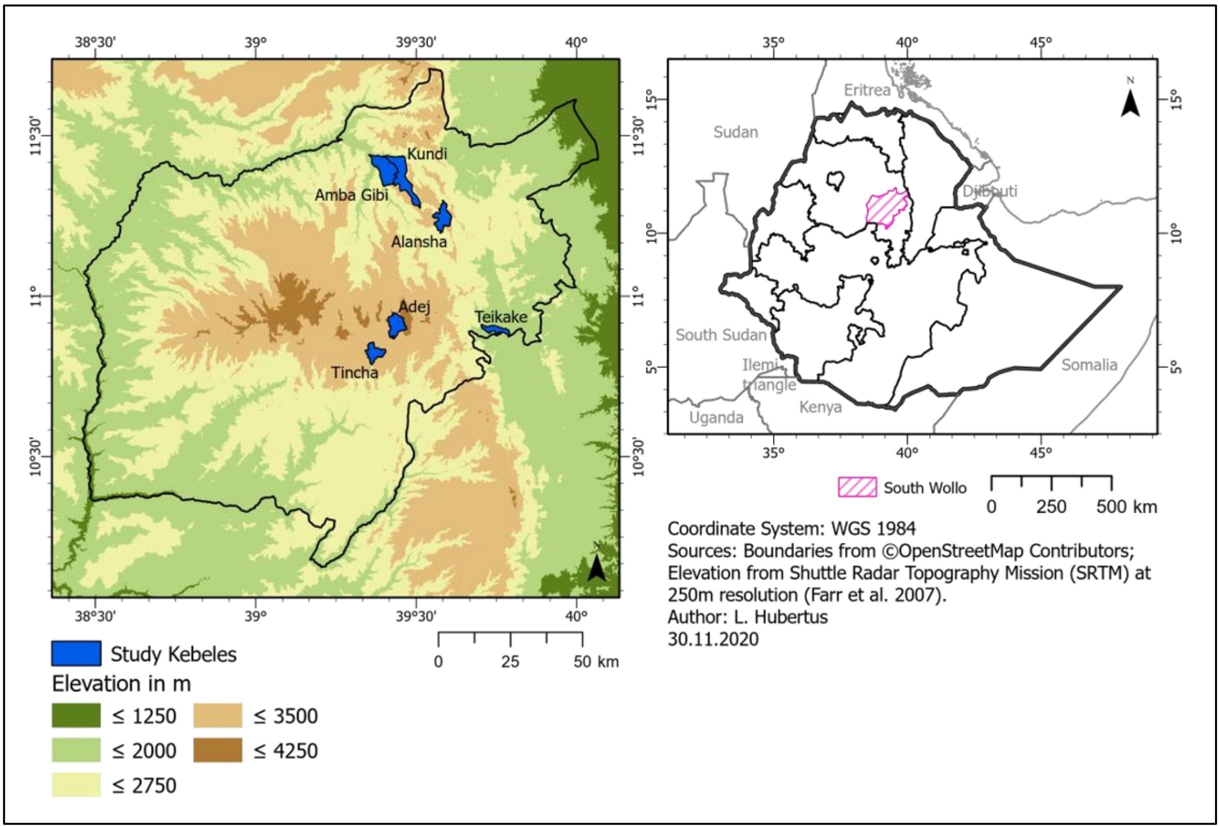

Figure 1 Maps of the location of South Wollo in Amhara Regional State in Ethiopia (right) and of the location of the study kebeles within South Wollo with elevation from Shuttle Radar Topography Mission (SRTM) at 250m resolution (Farr et al. 2007) (left).

Ethiopia, in the South Wollo Zone of the Amhara Regional State in the Northern Ethiopian highlands, located between about 10° 11' and 11° 43'N and between 38° 24' and 40° 01'E (figure 1). The largest city in the area is Dessie located about 400 km north of Ethiopia's capital Addis Ababa. It is a mountainous area where altitude and terrain strongly influence rainfall patterns and cropping activities. This results in the presence of three agroecological zones in the study area: Kola (1200 -1600 masl), Weyna Dega (1600 - 2600 masl) and Dega (2600-3600 masl) (Hurni 1998). In the high altitude parts of South Wollo, farmers refrain from cropping in the summer months and are fully dependent on the lighter spring rains due to low temperatures and intense rainfall, partly in the form of hail which can destroy crops (Groth et al. 2020; Hermans and Garbe 2019).

South Wollo's rainfall regime is characterized by three distinct seasons locally known as *kiremt*, the main rainy season from late June to September/October, *belg*, the small rainy season from February/March until May and the dry season, *bega*, during boreal winter (figure 3). Kiremt rains in Ethiopia are mainly caused by the northward migration of the intertropical convergence zone (ITCZ). Other influences include Arabian and Sudanese thermal lows developing along 20°N, high-pressure systems evolving and persisting over the South Atlantic and South Indian Ocean, the tropical easterly jet and the development of the low-level Somali jet (Seleshi and Zanke 2004). Kiremt rains cover most of Ethiopia and are the most important rainy season for

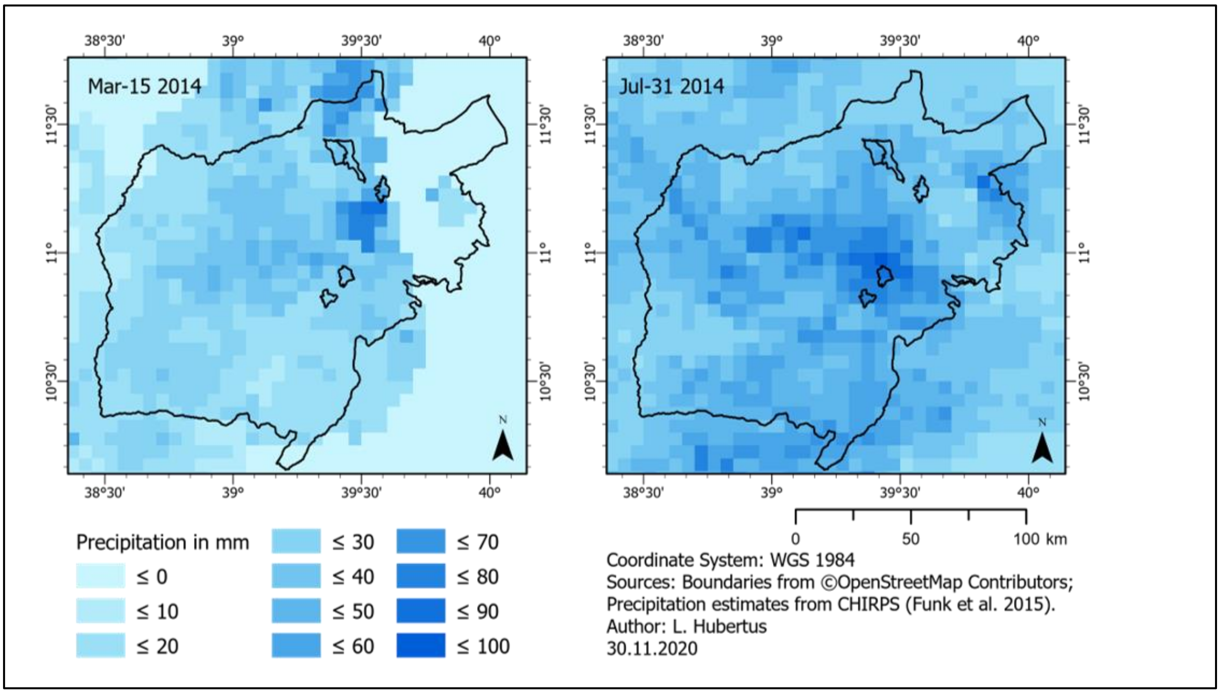

Figure 2 Map of the study area and CHIRPS precipitation estimates (Funk et al. 2015a) with example days for high precipitation during belg (left) and kiremt (right).

agricultural activities, as 90-95% of the country's cereal grains are grown in this period (Hermans-Neumann et al. 2017). Belg rains are mainly caused by the development of a thermal low (cyclone) over South Sudan and moist winds from highs in the Gulf of Aden and Indian Ocean being drawn into this center causing rains in parts of the Ethiopian highlands (Seleshi and Zanke 2004). Belg, in particular, is highly variable in the study area, both spatially due to the mountainous terrain and temporally (Alemu and Bawoke 2019). Bega is dominated by dry air masses originating from the Saharan anticyclone and/or high-pressure systems over central Asia extending into the Arabian Peninsula. Rainfall during bega is very rare, but is occasionally caused by low-pressure systems moving eastward from the Mediterranean and interacting with tropical systems (Seleshi and Zanke 2004). In figure 2, maps of the study area on an example day for each season show precipitation amounts and spatial distribution.

The livelihoods of the local farmers are characterized by mixed subsistence, rainfed and low input agriculture. Employment opportunities outside of agriculture are rare. They keep livestock, e.g. cows, goats, sheep or chicken, and grow mainly barley, wheat, teff, maize, pulses and sorghum (Groth et al. 2020). Livestock is an important asset for farmers in the study area and correlates with other indicators of welfare such as income, expenditures and food availability (Little et al. 2006).

In 1975, land in Ethiopia was nationalized by the Derg military government. It was distributed to households mainly based on family size. Land redistributions in Amhara happen regularly, with major redistributions having taken place in 1997 (Holden and Yohannes 2002). Farmers can acquire land through inheritance or through these centrally organized redistributions which have led to increasingly fractionalized landholdings and, due to a growing population, tenure has become a contentious issue for families and local communities (Ege 2017; Hermans and Garbe 2019; Morrissey 2013). As a consequence of the land scarcity, fallow land essentially does not exist (Hermans and Garbe 2019).

In addition to land being scarce, severe land degradation in the form of topsoil loss, gully erosion and declining soil fertility is a major risk to local farmers' livelihoods (figure 4) (Groth et al. 2020; Nyssen et al. 2004). Changing land use and land cover, mainly caused by poverty and a lack of agricultural intensification are the most important contributors to land degradation in the Ethiopian highlands (Nyssen et al. 2004). The lack of land combined with the increasing degradation is interlinked with farmers using steeper slopes for agriculture and intense grazing pressure (Bewket and Conway 2007). Large areas have become unsuitable for agriculture and soil fertility is decreasing, even though much has been done in the highlands in terms of soil and water conservation practices (Adimassu et al. 2017; Mekuriaw et al. 2018; Meshesha et al. 2014).

Although the literature on trends in droughts is not conclusive, it has been widely acknowledged that the effects of droughts have become increasingly severe given the variety of threats local farmers face (Little et al. 2006). Now, the Ethiopian highlands are regularly severely affected by famines, notoriously food insecure and have become heavily reliant on government and international aid, even in years with good rainfall (Groth et al. 2020; Little et al. 2006). People's ability to make a living in the face of these risks is challenging, even in comparison to other low-income parts of rural Africa (Little et al. 2006).

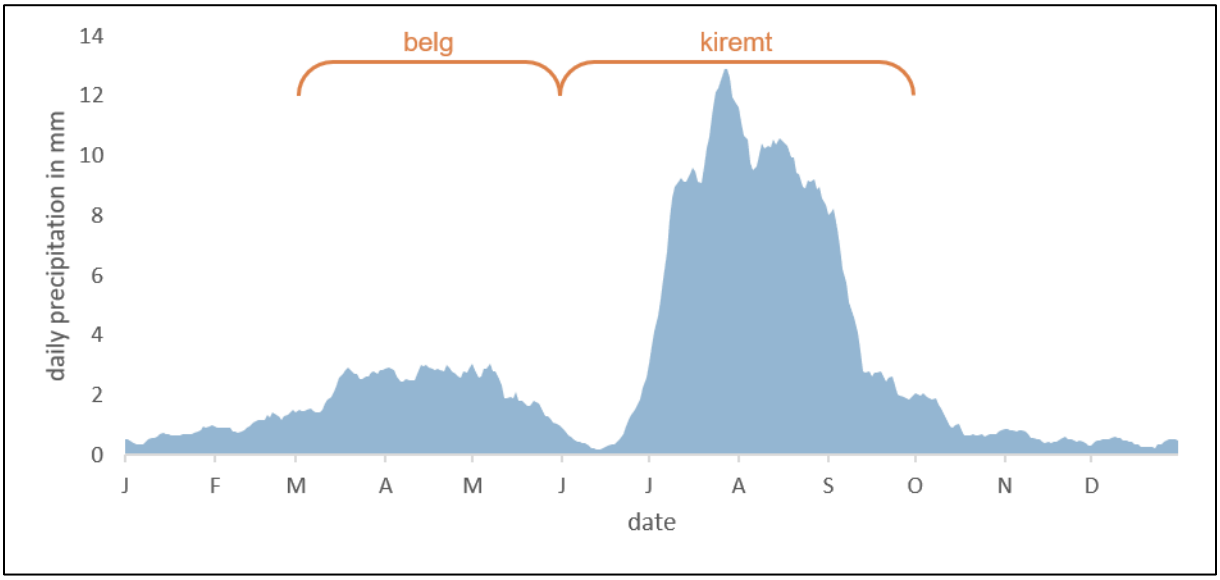

Figure 3 Rainfall regime in the study area. The graph shows the 10-day rolling mean of the mean daily precipitation in the six study kebeles between 1981 and 2017. Rainfall estimates are based on CHIRPS (Funk et al. 2015a). The small rainy season (belg) occurs between February and May and the main rainy season (kiremt) between June and October.

Figure 4 Photograph of the landscape in South Wollo with gully erosion. Photo credit: Juliane Groth.

3 Data

3.1 Research site selection

The selection of research kebeles and the collection of the interview data took place in the context of Groth et al. (2020) with a focus on environment-related migration. Four districts (*woreda*) within South Wollo were selected with the aim of purposively selecting a heterogenous sample of potential kebeles for further study: Legambo, Dese Zuria, Kutaber and Kalu. During a preparatory visit in April and May of 2017, district officials in agricultural offices were interviewed in order to get an overview of the kebeles in the respective districts regarding issues concerning livelihoods, major risks, coping and adaptation strategies. 19 kebeles were selected as potential research sites and visited to gather more detailed information on the situation in the kebeles. Village officials, mayors and/or religious leaders were asked in detail about their kebele compared to others in the area as well as differences within the kebele in terms of their key socioeconomic and environmental variables.

Based on the information gathered during the preparatory visit, a sample of six kebeles was selected as study sites with the aim of drawing a broadly representative sample of South Wollo.

Table 1 Details of the study kebeles as described by local officials (Groth et al. 2020).

Kebele	Agro-ecological zone	Belg	Kiremt	Own market	Asphalt road	Land degradation
Adej	Dega	x				High
Alansha	Dega	x	x		x	Low
Teikake	Kola	x	x			Low
Kundi	Kola		x	x	x	High
Amba Gibi	Weyna Dega		x			High
Tincha	Weyna Dega		x	x		Low

Figure 5 Photograph of the data collection showing a focus group discussion with village mapping. Photo credit: Juliane Groth.

The first variable included in the selection process is agroecological gradient (Kola (1200 - 1600 masl), Weyna Dega (1600 - 2600 masl), Dega (2600-3600 masl)), which is based on rainfall, cropping patterns and altitude (Hurni 1998). Second, land degradation (high and low severity) defined as a "reduced capacity of the soil and land to provide goods and services for human well-being mainly driven by soil erosion, i.e. gully erosion or the loss of topsoil and nutrients" (Groth et al. 2020). Third, two variables for remoteness were chosen: the presence of an asphalt road and/or a market within the kebele (Groth et al. 2020) (table 1).

3.2 Qualitative Interviews

In-depth fieldwork was conducted between November 2017 and February 2018 with eight to nine days spent in each kebele. The interviews were held in Amharic with the help of a local assistant who is from the region and familiar with fieldwork in local communities. During the first two days, three focus group discussions with five to seven participants were held in each kebele. The discussions lasted between three and four hours. The first group consisted of kebele officials (e.g. extension workers, religious leaders, head of administration). The second group was made up of heads of migrant households or their spouses and the third of heads of non-migrant households or their spouses. A migrant household was defined as a household where somebody had migrated outside of the kebele for at least one month within the last five years.

Focus groups were important for obtaining an overview of the specifics of local livelihoods and to build trust among the communities. Methods included wealth ranking, daily activity calendars, livelihood risk assessments, strategy ranking and mobility maps. Local officials were asked to map the kebele with its sub-kebeles and describe them according to the criteria relevant for site selection (figure 5). This was done to ensure that the part of the kebele selected for household interviews matched the previous classification from the selection process. Local officials also supported the identification of potential respondents for household interviews (Groth et al. 2020).

In an attempt to achieve a heterogenous sample of households, three migrant and three non-migrant households were selected, each with regards to their respective socioeconomic status (poor/medium/better-off). Since interviewees had to be able to recall the last decade, an age requirement of at least 30 years was adopted. In some cases, it became clear during the interview process, that a household had been mischaracterized and an additional household matching the characterization was sampled, leading to six to eight household interviews per kebele. The interviews followed a semi-structured approach with a list of guiding questions and consisted of three parts. First, the socioeconomic composition of the household was assessed, including main activities, land and crop management and personal characteristics of household members. Second, perceived changes in land degradation and rainfall were assessed, including how these changes affected the household's daily lives and the strategies to address them. The timeframe for these questions was 20 years and farmers were given the change in government in 1991 as a reference point. Third, migration experiences such as time span, destination, reasons for leaving and returning, financial and/or material transfers were assessed. In total, 18 focus group discussions and 42 household interviews are part of the dataset.

3.3 Rainfall estimates

The Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) is a quasi-global (50°S-50°N) dataset (Funk et al. 2015a). While CHIRPS data is available in a variety of temporal and spatial resolutions at the Climate Hazard Group's file transfer protocol (FTP) server (ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/), only data with a daily temporal resolution and a spatial resolution of 0.05° x 0.05° was used. In South Wollo, at latitudes between 10°N and 12°N, the grid cells offer a spatial resolution of approximately 5km x 5km. Data is available from 1981 to near-present. In order to correspond with the timeframe of the interview data collection, 31st December 2017 was determined as the last day of CHIRPS data to be considered.

CHIRPS was developed by the US Geological Survey (USGS) and the Climate Hazards Group at the University of California Santa Barbara. Three main data sources are used to calculate precipitation values: (1) the Climate Hazard group Precipitation Climatology (CHPclim), (2) satellite-based thermal infrared (TIR) precipitation estimates and (3) gauge observations (Dinku et al. 2018; Funk et al. 2015a). The CHIRPS calculation process is illustrated in figure 6 and explained below.

The first data source for CHIRPS, the CHPclim, is a monthly precipitation climatology based on precipitation normals from station data, monthly means of satellite surfaces calculated from

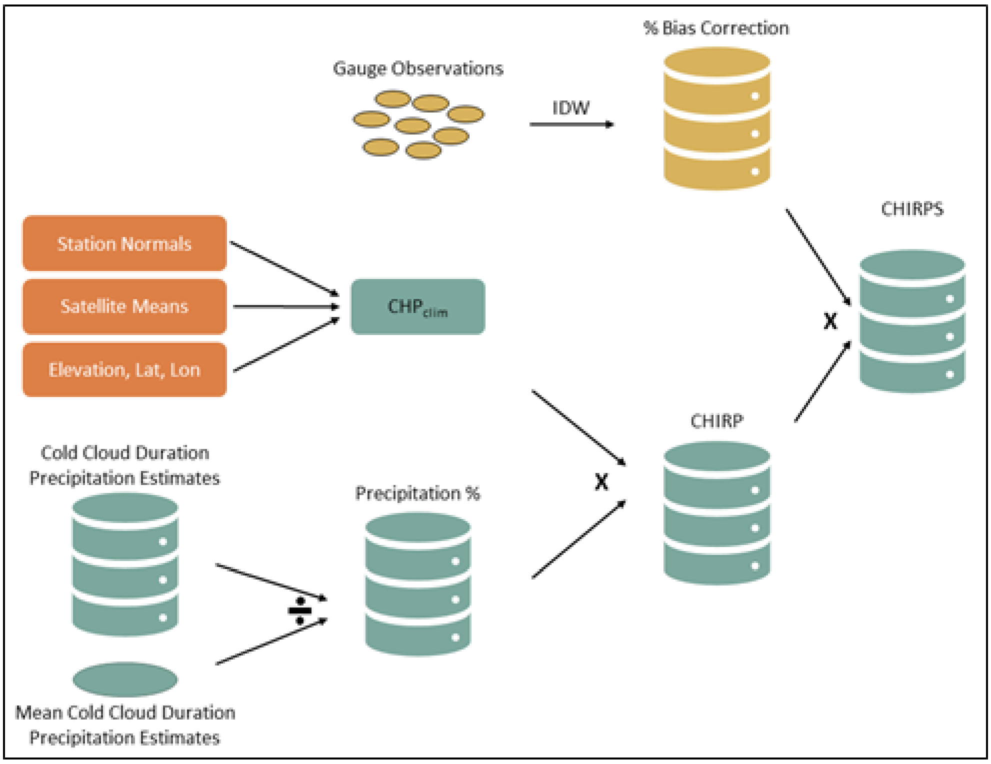

Figure 6 Overview of the CHIRPS calculation process. Modified from (Funk et al. 2015b)

five satellite products and topographic and physiographic surfaces based on elevation, latitude and longitude (Funk et al. 2015b). The satellite products used in the CHPclim are (1) the Tropical Rainfall Measuring Mission (TRMM) 2B31 microwave precipitation estimates (Huffman et al. 2007), (2) the Climate Prediction Center morphing method (CMORPH) microwave-plus-infrared based precipitation estimates (Joyce et al. 2004), (3) monthly mean geostationary infrared brightness temperature derived from multiple geostationary weather satellites (Janowiak et al. 2001), (4) Land Surface Temperature (LST) estimates derived from multispectral observations from Moderate Resolution Imaging Spectrometers (MODIS) (Wan 2008) and, after all these products were convolved into a common 0.05° grid, (5) the average of the CMORPH and TRMM precipitation fields was created as a fifth predictor (Funk et al. 2015b).

The second data source for CHIRPS, thermal infrared data, is retrieved from two global geosynchronous thermal infrared archives: the Globally Gridded Satellite (GriSat) and the NOAA Climate Prediction Center Dataset (CPC TIR). Pentad (five-day) rainfall estimates are calculated as the percentage of time during the pentad that the TIR observations show cold cloud tops (< 235°K). The cold cloud duration value is converted into millimeters of precipitation through previously determined local regression with Tropical Rainfall Measuring Mission Multi-satellite Precipitation Analysis version 7 (TRMM 3B42 v7) precipitation pentads (Funk et al. 2014). The pentadal precipitation estimate is then expressed as a fraction of normal by dividing each pixel's value by its long-term mean. This fraction is multiplied with the respective CHPclim value to produce the CHIRP estimate. The cold cloud duration values are thus used to estimate variations around the CHPclim mean in order to reduce systemic bias. Daily CHIRP values are disaggregates of the pentads (Funk et al. 2015a).

Finally, station data from more than 200 000 locations is blended with the CHIRP dataset to produce CHIRPS. The highest-quality station within a 5km radius is used as an anchor-station (N= 47 390) and missing values are filled with other sources within that distance. A modified inverse distance weighting method is applied to adjust CHIRP values with station data: for each grid cell in CHIRP, the five nearest stations are assigned a weight proportional to the square of their expected correlation. The closer a station, the higher the weight. The weights are scaled to sum 1 and used to blend the station data into a single ratio to adjust CHIRP estimates (Funk et al. 2014; Funk et al. 2015a).

CHIRPS has been validated over East Africa (Dinku et al. 2018; Gebrechorkos et al. 2018) and Ethiopia specifically (Ayehu et al. 2018; Bayissa et al. 2017) through comparison with gauge data and its performance has been compared with a number of other satellite-based rainfall products. In East Africa, CHIRPS outperformed the African Rainfall Climatology version 2 (ARC2) with higher skill and lower bias, the Tropical Applications of Meteorology using Satellite data (TAMSAT3), which performed better only at the daily timescale but contains considerable data gaps. CHIRPS was found to capture daily rainfall characteristics such as the number of wet days, duration of rainy seasons and total and daily rainfall well, although it was noted that correlation between station data and CHIRPS decreases with higher temporal resolution (Dinku et al. 2018; Gebrechorkos et al. 2018).

In the Upper Blue Nile Basin, which covers large parts of Amhara, CHIRPS also outperformed ARC2 and TAMSAT3 (Ayehu et al. 2018) as well as Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN), African Rainfall Climatology and Time-series (TARCAT) version 2 and Tropical Rainfall Measuring Mission (TRMM) (Bayissa et al. 2017). CHIRPS was found to be in good agreement with ground observations and showed excellent scores in bias and mean error at different timescales (Bayissa et al. 2017). Specifically in the Ethiopian highlands, CHIRPS showed reliable performance at different elevations during the wet seasons, even though satellite products tend to perform worse over mountainous terrain (Ayehu et al. 2018; Dinku et al. 2018). Since CHIRPS is available at a high spatial and temporal resolution including in countries where data is sparse or temporally incomplete such as Ethiopia, it is recommended for use in long-term climate studies and for drought monitoring (Bayissa et al. 2017; Gebrechorkos et al. 2018).

4 Methods

4.1 Rainfall Analysis

Based on a review of the literature and in correspondence with frequently mentioned rainfall-related issues by interviewees, rainfall trends and rainfall variability were analyzed by means of the indices explained below. An overview of all indices analyzed can be found in table 2. Rainfall analysis was conducted separately for the respective cropping seasons used, only two indices were additionally calculated for annual data. As mentioned in chapter 1.2.1, farmers perceive changes in rainfall primarily in terms of their agricultural activities that are more influenced by the rainy seasons and their timing than aggregate annual rainfall (Cochrane et al. 2020; Slegers and Stroosnijder 2008). The analysis was performed in *R (R Core Team 2020)*.

The rainfall indices are largely based on the recommended indices proposed by the Expert Team on Climate Change Detection and Indices (ETCCDI) which was established through a joint initiative by the Commission for Climatology (CCI) of the World Meteorological

Table 2 Summary of the rainfall indices used in the analysis.

index	**description**	**unit**
annual		
RR	total annual rainfall	mm
rd	number of rainy days (>1mm)	days
seasonal: calculated separately for belg and kiremt		
RR	total seasonal rainfall	mm
rd	number of rainy days (>1mm)	days
timing		
onset	onset of the rainy season (>15mm over three consecutive days)	day of year
offset	cessation of the rainy season (maximum seasonal cumulative anomaly)	day of year
dur	number of days between onset and cessation	days
dry spells		
CDD	maximum number of consecutive dry days	days
totdsl	total dry spell length	days
avgdsl	average dry spell length	days
intensity and extreme events		
SRA	standardized rainfall anomaly	-
Rx1day	maximum 1-day precipitation	mm
R99p	extremely wet days: percentage of wet days exceeding the 99th percentile of the period of observation	%
R95p	very wet days: percentage of wet days exceeding the 95th percentile of the period of observation	%
SDII	simple daily intensity index: total seasonal precipitation divided by the number of wet days	mm/day

Organization (WMO), the World Climate Research Programme project for climate variability and predictability (CLIVAR) and the Global Climate Observing System (GCOS). The aim was to form a set of internationally agreed upon indices to improve and harmonize monitoring of temperature and rainfall (Frich et al. 2002; Karl et al. 1999; Zhang et al. 2011). A list including all ETCCDI indices can be found at http://etccdi.pacificclimate.org/list_27_indices.shtml (as of Nov 5, 2020).

CHIRPS values were extracted for all six kebeles. The median value of all grid cells partially or fully within the official kebele boundaries was used as the precipitation estimate for the respective kebele on a given day, resulting in a time series of 13514 daily values over 37 years for each kebele. The indices were calculated for all kebeles based on these values and the mean value of the results was calculated for three groups of kebeles, differentiated by the cropping seasons farmers in these kebele used (belg only (BO), kiremt only (KO) or belg and kiremt (BK)). This distinction was necessary, since potential changes in rainfall can be very different for the rainy seasons, thus influencing cropping and perception of these changes in a very different way. Significant changing rainfall patterns for one season may be perceived as a very severe threat to their livelihood by respondents heavily relying on this season, whereas others may feel indifferent to these changes or not perceive them at all when their cropping activities are independent from said season. The three groups of kebeles are the one using only belg (Adej), those using both seasons (Teikake, Alansha) and those using only kiremt (Amba Gibi, Kundi, Tincha) (table 1).

The results for all indices were grouped into four timesteps: 1981-1990, 1991-2000, 2001-2010 and 2011-2017. The first three timesteps each span a decade while the last timestep consist of the remaining seven years. The last, shorter, period may lead to bias as there is less data incorporated into the calculations. For each timestep, the mean value, standard deviation and coefficient of variation (CV) were calculated to assess variability. CV is calculated as

$$CV = \frac{\sigma}{\bar{x}}$$

where σ is the standard deviation and $\bar{x}$ is the mean.

4.1.1 Rainy Seasons

The seasons were defined in two different ways: first, the rainy season was defined as the time between the calculated onset and the calculated offset of the rainy season (chapter 4.1.3). This definition was used for the indices related to timing (dur) and dry spells (cdd, totdsl, avgdsl), since a clearly defined onset and offset are particularly relevant to these indices. Dry spells can cause crop failure if they occur after rainy season onset: the seed dies due to a lack of precipitation early in the growing period or late in the season, i.e. the crops have not reached maturity when a dry spell ends the growing period (Rosell and Holmer 2007).

The second definition uses monthly periods based on literature from the region (Legese et al. 2018; Rosell 2011; Rosell and Holmer 2007). Belg is defined as the period from 1 February to 31 May and kiremt is defined as the period from 1 June to 31 October. This broader definition was applied to avoid potential errors from false onset or offset calculations, as these proved to be very difficult in the analysis process. The second rainy season definition was applied to general indices (RR, rd) and indices concerning rainfall intensity and extreme events (SRA, Rx1day, R99p, R95p, SDII). These indices are hardly affected by the exact timing of the rains, e.g. the maximum 1-day precipitation (Rx1day) will almost certainly be during the actual rainy period.

4.1.2 Total Rainfall and Rainy Days

Total rainfall (RR) was calculated for annual and seasonal data. As mentioned above, the rainy season definition by month was used. Let RR_{ij} be the daily precipitation amount for day i of period j, then total rainfall amounts are calculated (Frich et al. 2002):

$$RR_j = \sum_{i-1}^{I} RR_{ij}$$

A rainy day is defined as any day with CHIRPS precipitation estimates above 1 mm. In the literature, rainy day thresholds vary depending on study area, research objectives and data availability. Studies with a stronger focus on climatology or hydrology often use a rainy day threshold of 0.1 mm, as it is the minimum measurable amount for station data while studies looking at agriculture or perception on the other hand often use a higher threshold as miniscule amounts of rainfall are (almost) irrelevant for agriculture and the perceptions of local communities (De Longueville et al. 2020; Segele and Lamb 2005). Also, since the daily rainfall represents an average of all CHIRPS grid cells fully or partially within the kebele, a smaller threshold may lead to the data being susceptible to outliers within CHIRPS grid cells.

4.1.3 Timing of the Rainy Seasons

The indices concerned with timing of the rainy seasons include the start of the season (onset), the cessation of the season (offset) and its duration (dur). The determination of rainy season onset in the literature can follow several different procedures, depending on the region and data availability. For example, for the determination of the onset of the West African Monsoon, at least 18 definitions were found (Fitzpatrick et al. 2015).

Here, a threshold-based definition was used to determine rainy season onset, i.e. a specified amount of rainfall must occur over a specified time period. This is sometimes combined with an additional argument of an absence of dry spells in the following days. The onset definition as the first day of the year’s first wet-spell of three or more days with a total of 20 mm or more, provided there were no dry-spells of eight or more days in the subsequent 30 days, was established for kiremt rains in Ethiopia. For regions such as South Wollo, where spring rains might give an early onset of kiremt, only dates within two months of the climatological onset date were considered (Segele and Lamb 2005). The defined threshold might seem arbitrary, however it serves as a proxy for soil moisture and is appropriate for local agronomic studies (Lala et al. 2020; MacLeod 2018). Considering this study is comparing farmers' perceptions and rainfall data, it seems more appropriate to use a threshold-based definition, instead of, for example, definitions through rainfall anomalies, as farmers are unable to predict future developments of rainy seasons. It is also evident from the collected qualitative data that the agricultural decision-making process early in the season is largely based on soil moisture.

Determining the exact thresholds is not universal and must be done locally, particularly in areas with high spatial variability such as South Wollo. Based on the definition used by Rosell (2011), which was determined specifically for this area of the Ethiopian highlands, the onset was defined as the first day of the first wet-spell of at least 15 mm rainfall over three consecutive days. An additional criterion for dry spells was not taken into consideration, as there was no onset date found for different dry-spell criteria used in the literature for many years and dry spells are assessed separately in this analysis. In order to avoid onset detection during singular rainfall events in the dry season, the onset date was searched only within the months when the respective rainfall occurs: for belg between February and May and for kiremt between June and October (Rosell 2011; Rosell and Holmer 2007). Also, farmers are unlikely to plant outside the time when the rainy seasons usually occur (Lala et al. 2020; MacLeod 2018).

The determination of rainy season cessation proved extremely difficult in the analysis process. Segele and Lamb (2005) propose a threshold-based definition where the day before the first day of a dry-spell of at least 20 days is determined as the offset of the rainy season. This definition was developed for kiremt with the assumption that with the abrupt withdrawal of the ITCZ at the end of the rainy season, kiremt rains end and the determination of rainy season cessation is thus rather simple. Partially as a consequence of the CHIRPS interpolation process, but also due to the local characteristics of the rainfall in the study area, this definition proved insufficient for kiremt. For belg, a threshold-based cessation determination proved even less viable, as the temporal variability of belg is very high, the dry period between the rainy season varies and singular small rainfall events within this dry period are not uncommon. Thus, offset determination through rainfall anomalies, as first described for South America by Liebmann and Marengo (2001), rather than rainfall thresholds are chosen as the method for rainfall cessation determination. It has been successfully applied for onset and offset determination in Africa (Liebmann et al. 2012) and adapted for bimodal rainfall regimes (Dunning et al. 2016). The method is particularly appropriate to use locally and for gridded data such as CHIRPS and has proven robust across observational datasets (Dunning et al. 2016; MacLeod 2018). Since farmers are unlikely to plant outside the given window when the rainfall usually occurs and since belg rains proved to be too weak to facilitate the application of the procedure proposed by Dunning et al. (2016) for bimodal rainfall regimes, the calculation was applied to a window centered on each season, February-May for belg and June-October for kiremt (Lala et al. 2020; MacLeod 2018).

The underlying assumption of the method is, that precipitation during the rainy season exceeds its climatological annual average (Liebmann and Marengo 2001). First, the long-term mean rainfall $\bar{Q}_{belg}$ and $\bar{Q}_{kiremt}$ is calculated for the two seasons across all 37 observed years. Offset dates are then calculated for each individual year by computing the daily cumulative rainfall anomaly $A(D)$ on day D:

$$A(D) = \sum_{i=ons}^{D} R_i - \bar{Q}$$

where R_i is the rainfall on day i, and i ranges from the previously calculated onset date ons to the day D (Dunning et al. 2016). The day of the year when the cumulative rainfall anomaly $A(D)$ is at its absolute maximum is defined as the cessation day, as following that day relative accumulation is less than expected from climatology (Liebmann et al. 2012). Figure 7 from Lala et al. (2020) illustrates the onset and offset determination through the threshold method (for onset), the anomaly method with no window centered around the rainy season (yearly) and the anomaly method with the window around the rainy season for a unimodal rainfall regime in the Ethiopian highlands, i.e. kiremt rain only.

Although the rainfall regime in figure 7 knows no belg rain, it shows on the one hand the offset date at the maximum cumulative anomaly (mid-October in figure 7) and its determination

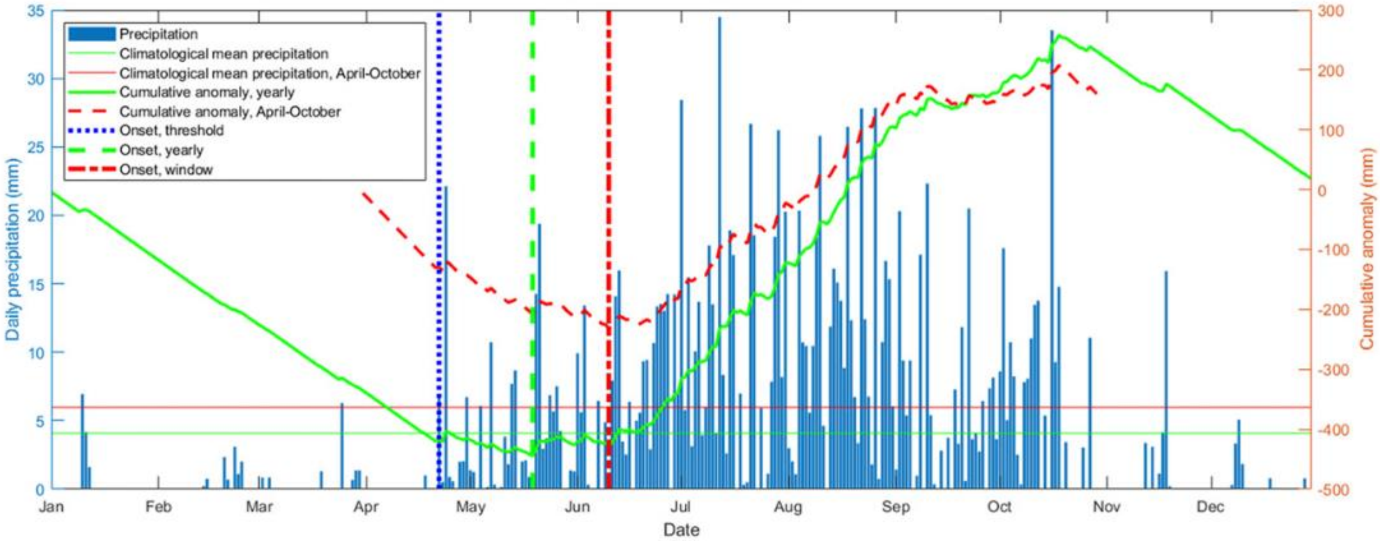

Figure 7 Daily Precipitation (left axis) and cumulative precipitation anomaly (right axis) for one year including long-term annual mean (green horizontal line), long-term window mean (red horizontal line) and respective cumulative anomalies. Onsets for threshold, yearly and window methods are shown as vertical lines (Lala et al. 2020).

before the last rainfall events of the year that are no longer part of the rainy season. This would make offset-determination through a threshold method as proposed by Segele and Lamb (2005) difficult. On the other hand, it also shows how determining the onset through the same method (window) compared to the threshold method (using the criteria by Segele and Lamb (2005) in figure 6) would move the determined onset date later into the season. This seems inappropriate in the context of this study, considering the amounts of rainfall between the onset date determined through the threshold and the date determined through the window method are quite substantial and would likely prompt agricultural activity by farmers (Lala et al. 2020).

The duration of the rainy season i in the year j was calculated as

$$dur_{ij} = offset_{ij} - onset_{ij}$$

which is simply the number of days between the determined onset and the determined offset date.

4.1.4 Dry Spells

Dry Spells can have devastating consequences for crops in the study area, especially early in the rainy season. For example, according to key informants in South Wollo, more than seven days in a row without rainfall after the onset of belg can completely destroy the growth of tef (Rosell and Holmer 2007). How devastating a dry spell is to crop growth and local farmers' food security depends on the crop itself as well as the growth stage the crop is in. For example, grain crops are usually more sensitive to dry periods in the time of flowering and grain filling (Sivakumar 1992).

The three dry spell indices are Consecutive Dry Days (CDD), total dry spell length (totdsl) and average dry spell length (avgdsl). A dry spell is defined as at least three contiguous dry days (RR < 1mm) between the previously calculated onset and cessation date (Segele and Lamb 2005). CDD is part of the widely used ETCCDI indices and is calculated as the maximum number of consecutive days when precipitation is less than 1 mm (Zhang et al. 2011). It is widely applied in Ethiopia for dry spell monitoring (Gebrechorkos et al. 2019a; Mohammed et al. 2018; Seleshi and Camberlin 2006). The other dry spell indices follow Segele and Lamb (2005), with totdsl representing the count of all days defined as a dry spell day and avgdsl the mean length of the dry spells for each season.

4.1.5 Intensity and Extreme Events

The indices for extreme events and rainfall intensity include four ETCCDI indices developed for monitoring extreme events: Rx1day, R95p, R99p and SDII (Frich et al. 2002; Zhang et al. 2011) as well as standardized rainfall anomaly (SRA). Extreme events such as heavy rainfall events and greater precipitation intensity are expected to increase in the process of global climate change, however different regional and local patterns, which require spatially adequate

Table 3 SRA classification (McKee et al. 1993; Alemu und Bawoke 2019)

SRA value	Category
SRA > 2.0	extremely wet
1.99 > SRA > 1.5	very wet
1.49 > SRA > 1.0	moderately wet
0.99 > SRA > - 0.99	near normal
- 1.0 > SRA > - 1.49	moderately dry
- 1.5 > SRA > - 1.99	severely dry
SRA < - 2.0	extremely dry

analysis, exist (Tebaldi et al. 2006). Analyzing extreme events is particularly relevant in the context of this study since they have been found to shape perceptions significantly (Debela et al. 2015).

Standardized rainfall anomaly (SRA) is used to determine wet and dry years in the record and allows for assessment of frequency and severity of droughts (Alemu and Bawoke 2019). SRA for the season i in the year j is calculated as

$$SRA_{ij} = \frac{P_{ij} - P_{mj}}{\sigma}$$

where P_{ij} is the total precipitation in season i in year j, P_{mj} is the mean precipitation in season i over the period of observation. σ is the standard deviation of precipitation over the period of observation (Agnew and Chappell 1999). Classification of SRA by McKee et al. (1993) can be found in table 3. Standardized rainfall anomalies are graphically represented in figure 9**,** which allows for evaluation of inter-annual fluctuations of rainfall in the study area over the 37 years observed (Ayalew et al. 2012).

Rx1day describes the maximum 1-day precipitation event in each season and is calculated as

$$Rx1day_j = \max{(RR_{ij})}$$

where RR_{ij} is the daily precipitation on day i in period j (Zhang et al. 2011). It is an absolute indicator for heavy rainfall events.

R95p and R99p are very similar indices, looking at very wet and extremely wet days as a percentage of all rainy days during the respective rainy season. They are calculated as

$$R95p_j = \sum_{w=1}^{W} RR_{wj} \; where \; RR_{wj} > \; RR_{wn}95$$

and

$$R99p_j = \sum_{w=1}^{W} RR_{wj} \; where \; RR_{wj} > \; RR_{wn}99$$

where RR_{wj} is the daily precipitation on a wet day w (*RR* > 1mm) in period j, W is the number of wet days in period j and $RR_{wn}95$ and $RR_{wn}99$ are the 95th and 99th percentile of precipitation on wet days in the period of observation. The indices represent the amount of rainfall falling above the 95th and 99th percentile and include the most extreme precipitation events in the respective season (Alexander et al. 2006).

The Simple Precipitation Intensity Index (SDII) measures the rainfall intensity, i.e. the amount of rainfall per rainy day and is calculated as

$$SDII_j = \frac{\sum_{w=1}^{W} RR_{wj}}{W}$$

where RR_{wj} is the precipitation on wet days w (*RR* > 1mm) in period j and W is the number of wet days in j (Frich et al. 2002; Zhang et al. 2011).

4.1.6 Mann-Kendall Trend Test and Sen's Slope Estimator

The non-parametric Mann-Kendall (MK) trend test (Kendall 1975; Mann 1945) and Sen's Slope estimator (Sen 1968) are widely used for climatological and hydrological time series data to detect trends and their magnitude. The MK test is particularly useful, as it uses only the relative magnitudes of the data instead of their measured values and the data need not conform to any particular distribution (Gilbert 1987). It is also considered robust against outliers (Mekonen and Berlie 2020).

Before performing trend analysis, the data was inspected for possible autocorrelations through visual examination of the results of the autocorrelation (*acf*) and partial autocorrelation (*pacf*) function in *R*. No autocorrelations were found. The MK test is calculated by first listing the data over time: $x_1, x_2, \dots, x_n$ where x_i is the datum at time i. The sign of all $n(n-1)/2$ possible differences $x_j - x_k$ is determined, where $j > k$, resulting in the differences $x_2 - x_1$, $x_3 - x_1, \dots, x_n - x_1, x_3 - x_2, x_4 - x_2, \dots, x_n - x_{n-2}, x_n - x_{n-1}$. The function $sgn(x_j - x_k)$ is an indicator function with the values 1, 0, or -1 according to the sign of $x_j - x_k$:

$$sgn(x_j - x_k)\begin{cases} = 1 \; if \; x_j - x_k > 0 \\ = 0 \; if \; x_j - x_k = 0 \\ = -1 \; if \; x_j - x_k < 0 \end{cases}$$

The Mann-Kendall statistic, i.e. the number of positive differences minus the number of negative differences, is then computed:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sgn(x_j - x_k)$$

A positive value of S indicates a positive trend, i.e. measurements taken later in time tend to be larger, and a negative value of S indicates a negative trend, i.e. measurements taken later in time tend to be smaller (Gilbert 1987). Since S is asymptomatically normally distributed, the mean and variance of S are calculated to account for possible ties in $x_j - x_k$ (Hipel and McLeod 1994; Kendall 1975):

$$E[S] = 0$$

$$Var[S] = \frac{n(n-1)(2n+5) - \sum_{j=1}^{p} t_j(t_j - 1)(2t_j + 5)}{18}$$

where p is the number of tied groups and t_j is the number of data points in the j^{th} tied group. By calculating mean and variance of S, it is possible to check whether S is significantly different from zero. The standard normal variate Z is consequently applied (Hipel and McLeod 1994):

$$Z = \begin{cases} \frac{S-1}{[Var(S)]^{1/2}}, if\ S > 0 \\ 0, \quad if\ S = 0 \\ \frac{S+1}{[Var(S)]^{1/2}}, if\ S < 0 \end{cases}$$

Kendall's rank correlation coefficient (tau) is expressed as $\tau = S/D$, where D is defined as the maximum possible value of S, which occurs when $x_1 < x_2 < \ldots < x_n$ (Hipel and McLeod 1994; Kendall 1975) and is calculated as

$$D = [\tfrac{1}{2}n(n-1) - \tfrac{1}{2}\textstyle\sum_{j=1}^{p} t_j(t_j - 1)]^{1/2}\ [\tfrac{1}{2}n(n-1)]^{1/2}.$$

All calculations for the MK trend test were performed in *R* (R Core Team 2020) using the *Kendall* package (McLeod 2011). Besides Kendall's tau, the package also computes S, D, $Var[S]$ and a two-sided p-value to test the null hypothesis H_0 (no trend) against the alternative hypothesis H_1 (upward or downward trend, depending on the sign of Z). If the p-value is below the significance level of $\alpha = 0.05$, the alternative hypothesis is accepted.

Since the MK test does not quantify the magnitude of the detected trends, Sen's slope estimator is calculated additionally. It shows the change per unit time and is more robust against errors or outliers in the data than the slope in a linear regression model (Gilbert 1987). First, N' slope estimates are calculated for each data pair:

$$Q = \frac{x_{i'} - x_i}{i' - i}$$

where $x_{i'}$ and x_i are the values at times i' and i where $i' > i$ with N' being the number of data pairs where $i' > i$. The median of the N' values of Q is Sen's slope estimator (Gilbert 1987; Sen 1968). Sen's slope estimator was calculated at the 95% confidence interval using the *trend* package in *R (Pohlert 2020; R Core Team 2020)*. Trend analysis was performed for all indices and seasons except for Standardized Rainfall Anomaly (SRA) as the MK test cannot be performed for variables with both positive and negative values.

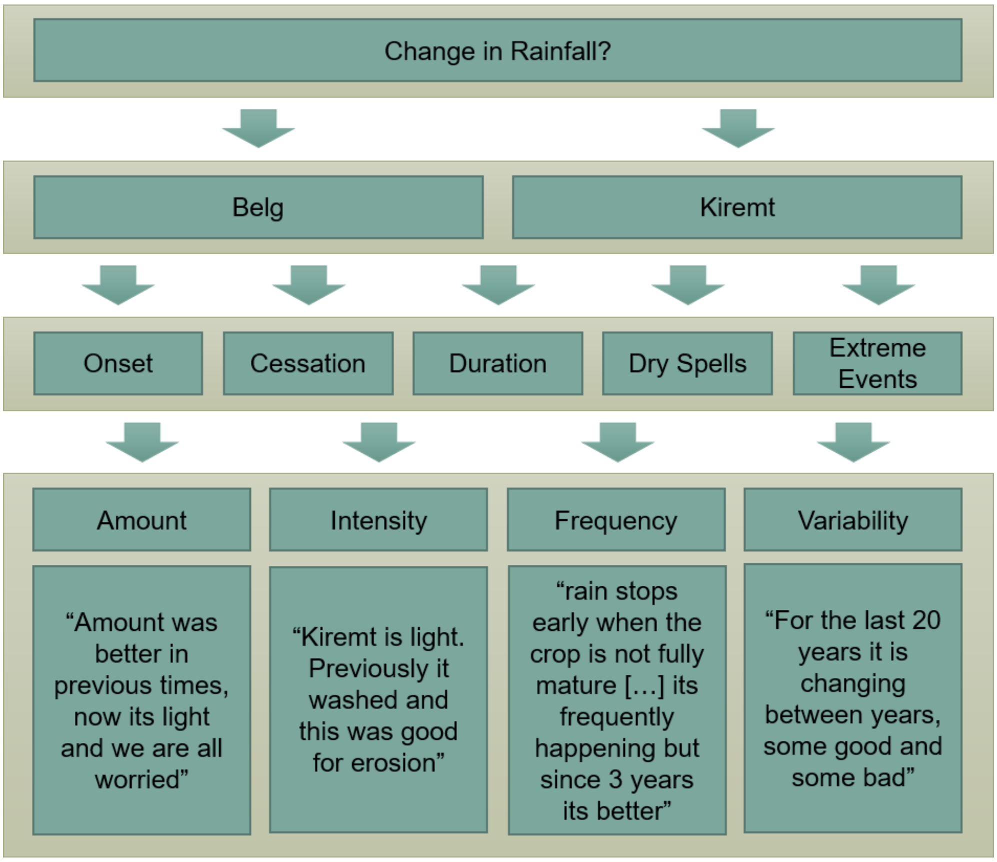

Figure 8 Flow chart for organizing and categorizing perceptions of rainfall changes from interview data including example quotes. Modified from Simelton et al. (2013).

4.2 Interview Analysis

The interview analysis was performed in MAXQDA. The 42 household interview and 18 focus group discussions were first grouped into the same kebele groups that were already used for rainfall analysis, i.e. belg only kebeles, kiremt only kebeles and kebeles using both cropping seasons. To ensure consistency and facilitate comparison between the perception data and the rainfall data, a framework similar to Simelton et al. (2013) was used to organize and contrast the data. The analysis process is illustrated in figure 8.

The interview data was analyzed in a multi-step process. First, it was assessed whether respondents had perceived changes in rainfall or not. This was true for almost all cases. The responses were then categorized according to the rainy season they relate to. This was of course particularly relevant in the kebeles where both rainy seasons are used for cropping as respondents differentiated between changes in the respective seasons. In the next step, the data was categorized according to what had changed in the perceptions of the farmers. This included dry spells, extreme events such as heavy rainfall and answers relating to the timing of the rainy seasons. The categories were not exclusive as respondents did not always distinguish between different aspects, e.g. an earlier cessation of the rainy season was often equated with shorter durations. In the last step, it was assessed how the rainfall had changed according to the respondents in terms of the amount of rain, its intensity, the frequency of changes occurring and whether the rain has become more or less variable (Simelton et al. 2013).

Additionally, the impacts of the perceived changes, e.g. declining yields, food insecurity or flooding were also assessed. Although only few respondents mentioned causes for the changes in rainfall, these were also coded. In order to improve contextualization of the data, other issues that were not directly related to rainfall changes such as land degradation, frost or weed infestation were also assessed. Farmers deployed various strategies to adapt to and cope with the threats to their livelihoods, including changing rainfall. These strategies were also coded and will be discussed, although in a limited manner as the data does not provide sufficient information on adaptation and coping strategies and it is not the central focus of this study.

5 Results

5.1 Rainfall Analysis

Tables with results for mean, standard deviation and CV in four timesteps as well as tables with results from the Mann-Kendall trend test are featured occasionally in this section. For complete results for all indices, rainy seasons and kebele groups, please refer to annex A for mean and variability and to annex B for trend test.

5.1.1 Annual Indices

The two annual indices analyzed were total rainfall (RR) as well as the number of rainy days (rd). These indices give an overview of the situation but since cropping activities are dependent on seasonal rainfall, they do not allow for detailed analysis. Table 4 shows the mean values ($\overline{x}$), standard deviations (σ) and coefficients of variation (CV) for annual total rainfall in four timesteps.

The results for total annual rainfall (RR) when compared over the time periods show slightly higher variabilities in the 1980s and in the 2010s. These are also the decades when the most severe droughts occurred in the study area (the droughts occurred in 1984 and 2015, for more details in chapter 5.1.2). Comparing the results between Kebeles, the results show generally higher amounts of rainfall in the kebele using belg only compared to the other kebeles. Results of the Mann-Kendall trend analysis can be found in table 6. As the results in table 4 already suggest, there are no statistically significant trends in total annual rainfall in either type of kebele.

Table 4 Results for indices calculated at the annual level including mean ($\bar{x}$), standard deviation (σ) and coefficient of variation (CV) for the three groups of kebeles: those using only belg for cropping (BO), those using both seasons (BK) and those using only kiremt (KO).

			1981-1990	1991-2000	2001-2010	2011-2017
RR	BO	$\bar{x}$	1148.38	1311.87	1198.55	1225.29
		σ	201.70	181.30	153.41	271.51
		CV	0.18	0.14	0.13	0.22
	BK	$\bar{x}$	1005.12	1140.91	1019.07	1042.72
		σ	155.50	123.79	105.72	201.79
		CV	0.15	0.11	0.10	0.19
	KO	$\bar{x}$	939.18	1084.57	987.57	1040.38
		σ	150.21	134.47	123.07	207.05
		CV	0.16	0.12	0.12	0.20
rd	BO	$\bar{x}$	73.60	69.00	67.10	76.00
		σ	20.55	9.45	9.01	9.40
		CV	0.28	0.14	0.13	0.12
	BK	$\bar{x}$	63.25	66.65	66.35	71.21
		σ	12.96	8.11	6.80	7.04
		CV	0.20	0.12	0.10	0.10
	KO	$\bar{x}$	69.40	69.90	66.90	71.43
		σ	15.02	6.55	9.30	7.48
		CV	0.22	0.09	0.14	0.10

The number of rainy days is on average between 66 and 76 per year. In all kebeles, the 1980s were the most variable in terms of rainy days. In the 1990s and 2010s, all kebele groups show very similar numbers. In the kebeles using only belg for cropping, rainy days were more numerous in the 1980s and 2010s. Considering the 1980s were also the period with the lowest annual rainfall and the highest variability in both rainfall amount and the number of rainy days, the data suggest less intense and more variable rainfall in this period compared to the later decades. The kebeles using only kiremt had very similar numbers of rainy days throughout the period of observation, with a slight increase in the 2010s, which may be caused by the lower number of years incorporated into this data. The kebeles using both cropping seasons however have seen an increasing number of rainy days throughout the period of observation, with stagnating numbers in the 1990s and 2000s. In fact, this trend is also reflected in the Mann-Kendall test results where the number of rainy days for this kebele group shows a statistically

Table 5 Mean percentage of total annual rainfall (1981-2017) each season receives per kebele group.

	Feb-May rain (belg)	Jun-Oct rain (kiremt)	Nov-Jan rain (bega)
BO	20.88	75.49	3.64
BK	26.21	67.89	5.90
KO	23.06	72.02	4.92

Table 6 Results of the Mann-Kendall trend test (tau) and Sen's slope estimator for the indices calculated at the annual level for the three groups of kebeles. Statistically significant trends at the 95% confidence interval (p < 0.05) are marked in bold font.

		tau	p	Sen's Slope
RR	BO	0.1201	0.3015	2.5359
	BK	0.0390	0.7437	0.8466
	KO	0.1231	0.2894	3.0321
rd	BO	0.0530	0.6562	0.1188
	BK	**0.2293**	**0.0482**	**0.3333**
	KO	0.0332	0.7835	0.0423

significant increasing trend at the annual level (table 6). Sen's slope estimator suggests an average increase of ⅓ day per year.

Other than the annual indices, seasonal indices will be explored only for the relevant kebele groups. In order to correspond better with the perception analysis, rainfall analysis for each season was only performed for kebeles where the respective season is used for cropping. This results in only two out of the three kebele groups shown per season. The seasons make up different proportions of the total annual rainfall as shown in table 5: belg contributes between 21% and 26% to the total annual rainfall and kiremt contributes between 68% and 75%.

5.1.2 Standardized Rainfall Anomaly (SRA)

The results for Standardized Rainfall Anomaly (SRA) are interpreted according to the classification by McKee et al. (1993) (table 3) and were applied to Amhara by Alemu and Bawoke (2019). Results are visualized in figure 9.

Between 25 and 28 of the 37 years analyzed are classified as near normal, depending on the kebele group. For belg, five years are classified as one of the three wetter categories by the SRA classification in table 3 (1983, 1987, 1993, 1995 and 1996). The high-altitude kebele using only belg for cropping received slightly wetter belg years than the kebeles using both seasons. The three drier classes however occur six times in the BO kebele and only four times in the kebeles using both seasons. The most severe droughts for belg are found in 1999 and 2008. In the kebeles using both seasons for cropping, these years are classified as extremely dry, while being classified severely dry in the belg only kebele. This shows that in the kebeles using both seasons for cropping, extreme droughts were more severe, however the belg only kebele received more dry years overall.

The SRA results for kiremt differ considerably from the belg results. In the kebeles using both seasons, six years were classified as wet: 1988, 1994, 1998, 1999, 2000, 2016. These same years fall into the wetter categories for the kebeles using kiremt only in addition to 2017. There is no overlap with the wetter belg years, in fact, the year 1999 is classified as wet during kiremt while being severely dry during belg. There are no differences in classification when it comes to dry years between the kebele groups. 1984 was extremely dry, 1987 and 2015 severely dry and 1982 and 1983 moderately dry, i.e. there were three consecutive dry years in the early

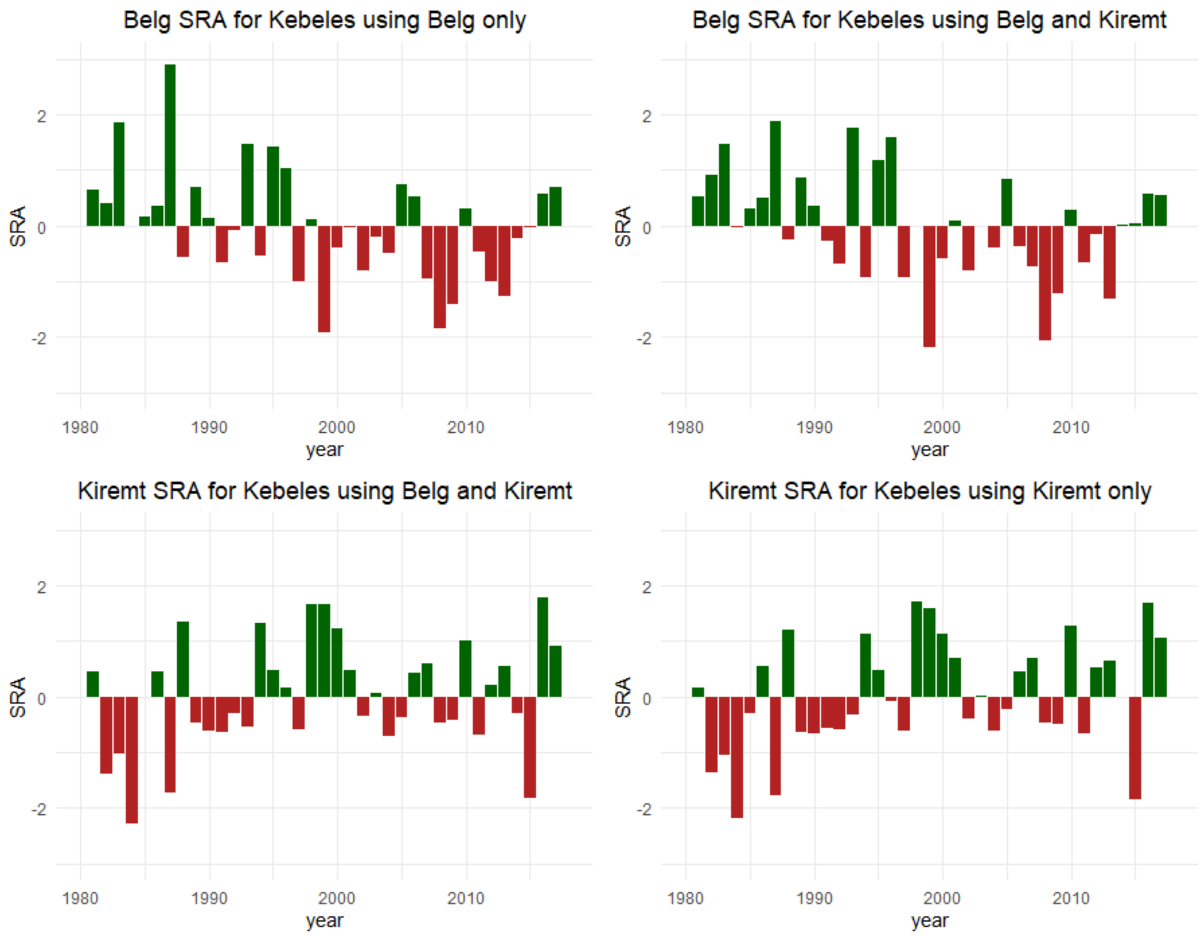

Figure 9 Seasonal results for standardized rainfall anomaly (SRA) for all kebele groups and rainy seasons.

1980s. Again, it is notable that the years 1983 and 1987 are some of the wettest years during belg and some of the driest years during kiremt.

These findings are consistent with literature correlating seasonal rainfall in the northern Ethiopian highlands with interactions between ocean and atmosphere in the Pacific Ocean known as the El Niño – Southern Oscillation (ENSO) phenomenon indicated by warm sea surface temperature anomalies in the tropical Pacific and the opposite event known as La Niña. Belg rains correlate positively with warm ENSO years and negatively with La Niña events, i.e. increased rainfall during ENSO and deficient rainfall during La Niña while kiremt rains show the opposite pattern (Fekadu 2015; Getahun and Shefine 2015; Seleshi and Demaree 1995). The results show this pattern in 1983, 1987 (ENSO) and 1999 (La Niña) for both seasons. The very wet 1998 kiremt season however is an outlier, as this was a strong ENSO year (Wolter and Timlin 2011).

Table 7 Results for total rainfall and rainy days during belg including mean ($\bar{x}$), standard deviation (σ) and coefficient of variation (CV) for the kebele groups using belg for cropping (BO and BK).

			1981-1990	1991-2000	2001-2010	2011-2017
RR	**BO**	$\bar{x}$	301.01	243.34	214.53	227.71
		σ	80.84	88.12	67.69	59.14
		CV	0.27	0.36	0.32	0.26
	BK	$\bar{x}$	323.56	262.39	236.23	260.12
		σ	52.52	101.58	66.37	53.35
		CV	0.16	0.39	0.28	0.21
rd	**BO**	$\bar{x}$	22.40	15.30	14.10	17.29
		σ	10.71	5.87	2.69	3.86
		CV	0.48	0.38	0.19	0.22
	BK	$\bar{x}$	20.95	15.20	15.65	18.07
		σ	7.60	5.75	2.86	1.54
		CV	0.36	0.38	0.18	0.09

5.1.3 Seasonal Total Rainfall and Rainy Days

Belg

The results for belg for both kebele groups in table 7 show similar tendencies, with BK kebeles receiving more rainfall than the one using only belg for cropping. Total rainfall amounts were higher in the 1980s and showed a decline in the following two decades and increasing amounts in the 2010s. The results show little variability in the 1980s, but highly variable rainfall (up to CV=0.39) in the following decade with a steady decline in CV since the 1990s. This development is more pronounced in the BK kebeles. These results are inconsistent with the findings from annual data, where variabilities in the 1980s and 2010s where the highest and total rainfall amounts, particularly in the 1980s, were lower. These findings confirm the results from the SRA and underline the conclusion, that the lower rainfall in the 1980s affected kiremt rains.

The pattern of the development over time for total belg rainfall repeats itself in the rainy days index. In the BO kebele, most rainy days during belg are observed in the 1980s with 22.4 rainy days between February and May. These numbers declined in the 1990s and 2000s to a low of 14.1 rainy days before increasing to 17.3 rainy days in the 2010s, thus not going back to 1980s levels. The kebeles using both seasons for cropping show a similar development. Other than the average number of rainy days, variabilities, however, have declined over the period of observation. The number of rainy days during belg has become less variable, a development that can also be observed for total belg rainfall apart from the 1980s.

The results from the Mann-Kendall trend test in table 8 show a statistically significant negative trend for total belg rainfall in the kebele using belg only. While a similar trend also exists for kebeles using both seasons for cropping, it is not statistically significant at the 95% confidence

Table 8 Results of the Mann-Kendall trend test (tau) and Sen's slope estimator for total rainfall and rainy days during belg for the two kebele groups using belg for cropping. Statistically significant trends at the 95% confidence interval (p < 0.05) are marked in bold font.

		tau	p	Sen's Slope
RR	**BO**	**-0.2462**	**0.0330**	**-2.6589**
	BK	-0.2222	0.0545	-2.3490
rd	BO	-0.1249	0.2934	-0.0801
	BK	-0.0640	0.5911	-0.0359

interval. The average annual decline in rainfall amounts during belg at around 2.7 mm must not be underestimated: farmers received on average more than 1% less rainfall every year over the 37 years observed. There are no statistically significant trends for the number of rainy days during belg.

In sum, the total rainfall amounts during belg have declined over the period of observation with a significant decline in kebele where farmers use only belg for cropping. Total rainfall amounts during belg have been highly variable in the 1990s and 2000s. The number of rainy days during belg has not significantly changed, however it has become less variable since the 1980s.

Kiremt

Total rainfall during kiremt, between June and October, is unsurprisingly much stronger than during belg as shown in table 9. The two kebele groups show very similar results. Both received the least rain in the 1980s, the decade in which multiple severe droughts occurred during kiremt as shown in the SRA results, and the most rain in the 1990s. The fact that the lower rainfall amounts in the 1980s are mainly a result of failing kiremt rains in this period is again shown in the results. Kiremt total rainfall variability is moderately high in the 1980s and 2010s, but lower in the decades in between. However, the variability of total belg rainfall exceeds that of kiremt. The results of the Mann-Kendall trend test in table 10 show a statistically significant increasing

Table 9 Results for total rainfall and rainy days during kiremt including mean ($\bar{x}$), standard deviation (σ) and coefficient of variation (CV) for the kebele groups using kiremt for cropping (KO and BK).

			1981-1990	1991-2000	2001-2010	2011-2017
RR	**KO**	$\bar{x}$	627.36	809.99	743.22	769.20
		σ	172.47	159.28	101.24	204.63
		CV	0.27	0.20	0.14	0.27
	BK	$\bar{x}$	627.70	808.76	716.72	735.71
		σ	174.87	156.81	85.46	194.64
		CV	0.28	0.19	0.12	0.26
rd	**KO**	$\bar{x}$	41.00	45.70	44.13	46.86
		σ	11.80	8.13	7.58	9.07
		CV	0.29	0.18	0.17	0.19
	BK	$\bar{x}$	35.55	43.60	42.05	45.00
		σ	10.50	9.18	6.26	7.61
		CV	0.30	0.21	0.15	0.17

Table 10 Results of the Mann-Kendall trend test (tau) and Sen's slope estimator for total rainfall and rainy days during kiremt for the two kebele groups using kiremt for cropping. Statistically significant trends at the 95% confidence interval (p < 0.05) are marked in bold font.

		tau	p	Sen's Slope
RR	BK	0.2012	0.0819	4.4125
	KO	**0.2643**	**0.0221**	**6.1692**
rd	**BK**	**0.2384**	**0.0410**	**0.2981**
	KO	0.0995	0.3950	0.1350

trend of total kiremt rainfall for kebeles using kiremt only. On average, these kebeles received over 6 mm more rain per year in the 37 years observed. This trend also exists in the kebeles using both seasons for cropping, however it is less pronounced and not statistically significant at the 95% confidence level.

The number of rainy days during kiremt is between two and three times higher than during belg. The KO kebeles receive slightly more rainy days than the BK kebeles throughout all timesteps. The variability of the number of rainy days during kiremt does not differ much between the two kebele groups. While it has been moderately variable in the 1980s, CV has not exceeded 0.21 in the following decades. The Mann-Kendall trend test shows a statistically significant positive trend in the number of rainy days received by kebeles using both cropping seasons. This trend is far weaker and not statistically significant in the kebeles using only kiremt and mirrors the trend that was already detected in the annual number of rainy days.

The amount of rainfall during kiremt has increased in parts of the study area while belg rainfall has decreased. In fact, the annual increase in kiremt rain was almost at the same magnitude as the decrease in belg rain. Kiremt was more variable in the 1980s and 2010s, the decades where SRA has shown the most severe droughts in the study area. While belg amounts have always been highly variable in the study area, there has been a decrease in belg variability.

5.1.4 Timing

Belg

Results for the indices on the timing of belg can be found in table 11**.** The onset of belg in kebeles using both rainy seasons is slightly earlier than in the kebele using only belg. CV ranges between 0.18 and 0.35 which demonstrates high variability of belg onset, however, since the 1990s, the onset of belg has become less variable in both kebele groups. The development of belg onset over time shows a statistically significant positive trend (table 12), which means the day of the year when belg starts is increasingly late. In the 1980s, belg started on the 52nd and 50th day of the year in belg only and belg and kiremt kebeles, respectively,

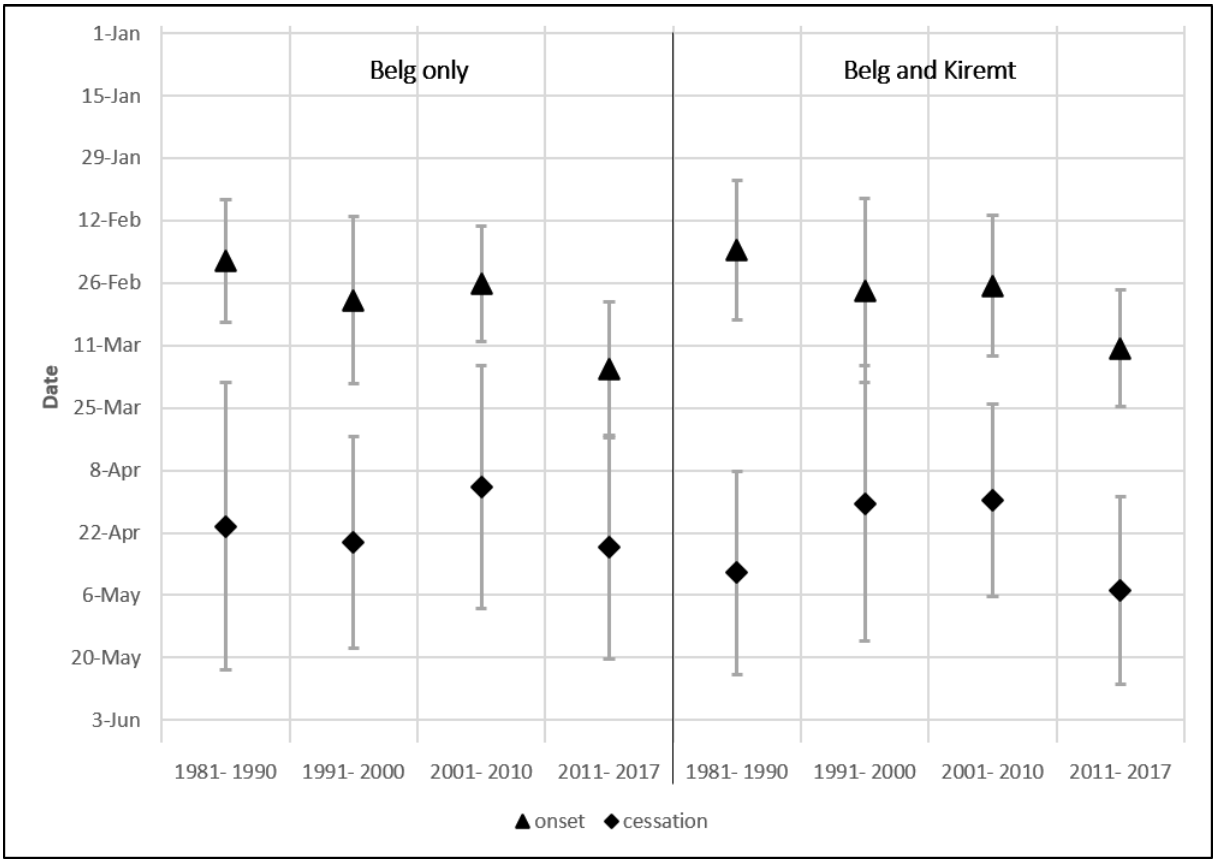

Figure 10 Onset and cessation of belg with standard deviations in four timesteps for the kebeles where belg is used for cropping.

which is between 19 and 21 February in the Gregorian calendar. This date has moved forward at a rate of 0.69 and 0.55 days per year in the respective kebele group according to Sen's slope estimator. By the 2010s, belg started at the 72nd and 76th day of the year, i.e. on 13 and 17 March in a non-leap year. Even though it has become less variable, belg rains are starting almost one month later than they used to 30 years earlier. The onset and cessation of belg are illustrated in figure 10.

The cessation of belg does not show any significant trends over time. In the kebele using only belg, it has been between the 112th and 116th day of the year, i.e. in late April, in three of the four timesteps observed, it was about 10 days earlier only in the 2000s. In the kebeles using both cropping seasons, the cessation of belg was later in the 1980s and 2010s (as late as the first week of May) than in the decades in between when belg ended around 16 April. The variability of the cessation of belg, although still quite high between CV=0.17 and CV=0.29, was not as high as the variability of the onset. In the kebeles using both cropping seasons, the end of belg rains has become less variable since the 1990s.

With belg starting significantly later and ending at around the same time, one would expect the duration of belg to be declining. While this trend does exist at about the same magnitude in both kebele groups, it is not statistically significant at the 95% confidence interval. In the 1980s,

Table 11 Results for the timing indices during belg including mean ($\bar{x}$), standard deviation (σ) and coefficient of variation (CV) for the kebele groups using belg for cropping (BO and BK).

			1981-1990	1991-2000	2001-2010	2011-2017
onset	**BO**	$\bar{x}$	52.00	60.90	57.20	76.43
		σ	13.70	18.77	12.88	15.31
		CV	0.26	0.31	0.23	0.20
	BK	$\bar{x}$	49.65	58.70	57.65	71.64
		σ	15.72	20.73	15.85	13.00
		CV	0.32	0.35	0.27	0.18
offset	**BO**	$\bar{x}$	111.60	115.20	102.70	116.29
		σ	32.18	23.73	27.18	25.10
		CV	0.29	0.21	0.26	0.22
	BK	$\bar{x}$	121.90	106.45	105.60	125.93
		σ	22.79	30.83	21.55	20.92
		CV	0.19	0.29	0.20	0.17
dur	**BO**	$\bar{x}$	60.60	55.30	46.50	40.86
		σ	29.79	32.49	31.48	29.66
		CV	0.49	0.59	0.68	0.73
	BK	$\bar{x}$	73.25	48.75	48.95	55.29
		σ	22.43	36.49	24.86	23.68
		CV	0.31	0.75	0.51	0.43

the duration of belg was the longest for both kebele groups, at 61 and 73 days respectively. While belg duration has been steadily declining in the kebele using only belg to around 41 days in the 2010s, it has been stagnating in the kebeles using both cropping seasons throughout the 1990s and 2000s before increasing again in the 2010s.

What is most noticeable about the duration of belg, however, is its variability. CV values are extremely high, with the lowest values at 0.31 going up as high as 0.75. This is where the methodological issues with onset and offset determination are the most visible. When looking at the driest years for belg in the SRA results, the extreme drought in 1999 stands out as well as the fact that between 2007 and 2013, only one year was not classified as dry. Some of these extremely dry years such as 1999 essentially mean a complete failure of belg rains for cropping activities. When rain is that scarce, onset is possibly determined through a singular rainfall day within a very dry season. Since cumulative anomalies will not increase considerably

Table 12 Results of the Mann-Kendall trend test (tau) and Sen's slope estimator for the timing indices during belg for the two kebele groups using belg for cropping. Statistically significant trends at the 95% confidence interval ($p < 0.05$) are marked in bold font.

		tau	p	Sen's Slope
onset	BO	**0.2736**	**0.0185**	**0.6883**
	BK	**0.2805**	**0.0155**	**0.5526**
offset	BO	-0.0136	0.9166	-0.0623
	BK	0.0030	0.9896	0.0000
dur	BO	-0.2121	0.0688	-0.7454
	BK	-0.1687	0.1464	-0.7670

after that event, as little to no rain is following it in the upcoming days, this singular rainfall event will be classified as the rainy season leading to durations of two or three days. In both kebele groups, there are only few years where this is the case. In the kebele using only belg, this concerns the years 1988, 1999, 2008 and 2013. In the kebeles using both cropping seasons, it is true in 1994, 1999 and 2008. The years appearing in both kebele groups, 1999 and 2008, were in fact the driest years for belg throughout the period of observation and the remaining years were also drier than normal. When the number of rainfall events during an extremely dry year is so low, the determination of onset and offset through the methods used here should be interpreted very carefully. It is likely that for agricultural activities, belg rain in these years can be considered a complete failure. The already high variability of belg duration will be severely affected by these outliers and should be interpreted as such.

The results for the timing of belg are similar for the kebele groups using this season for cropping. Belg rains start increasingly late, in the 2010s the onset was almost an entire month later than in the 1980s. The cessation date has not experienced a similar change over time. When interpreting indices for the timing of belg, methodological issues must be considered as very dry years can easily skew the results. Variability of belg timing is very high across all indices and has been declining since the 1990s for onset in both and cessation in one kebele group.

Kiremt

Compared to belg, the results for the timing of kiremt are very different. The onset of kiremt is almost identical in the two kebele groups using this cropping season throughout the period of observation. While kiremt rains started around the 187^{th} day of the year in the 1980s and 2010s, i.e. 6 July in a non-leap year, it was about a week earlier in the decades in between. Variability of kiremt onset is very low and almost identical for all kebele groups and timesteps, around CV=0.06. Results for kiremt timing are illustrated in figure 11.

Cessation of kiremt in both kebele groups has been earlier in the 1980s, when the rains ended on average in the last week of August. In the following decades, the cessation of kiremt is between the 248^{th} and the 258^{th} day of the year, i.e. between 5 and 15 September. In the 1980s, variability of kiremt cessation was at about 0.1, while it showed very low variability in the following decades. The higher variability in the 1980s can be explained through an outlier in 1984, a year with extreme drought during kiremt, when kiremt cessation was determined in the week after the onset and some less pronounced outliers in the drought years of 1983 and 1987.

This pattern carries through to the duration index. Kiremt was around 20 days shorter and more than twice as variable in the 1980s than in the later decades, when the duration stagnated around 70 days and CV was between 0.12 and 0.2. As mentioned above, the reasons for this

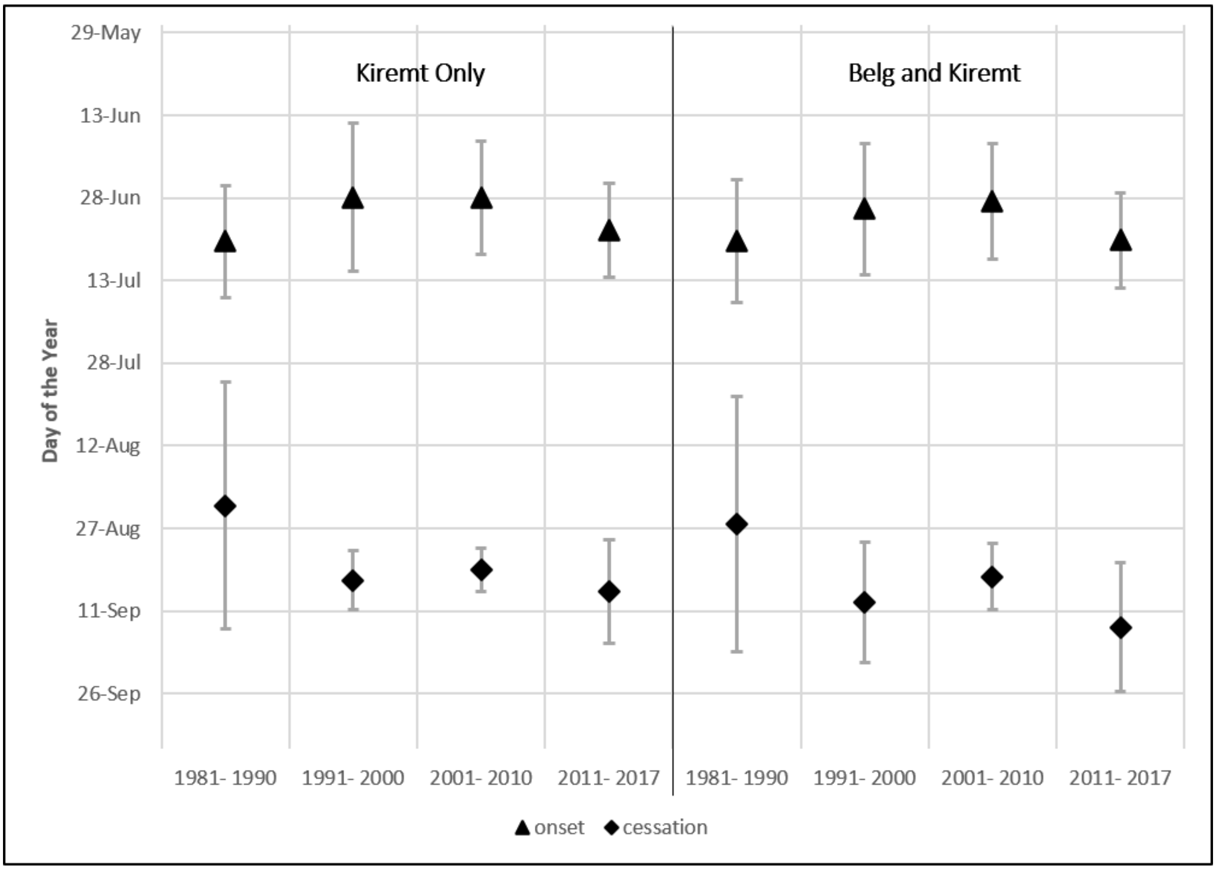

Figure 11 Onset and cessation of kiremt with standard deviations in four timesteps for the kebeles where kiremt is used for cropping.

are in part due to methodological issues as the offset and thus duration determination in the drought year 1984 produced similar outcomes as 1999 or 2008 during belg. In 1983 and 1987 however, duration in BK and KO kebeles was between 37 and 42 and between 21 and 22 days, respectively. In these years, the method was able to capture the rainy period quite well, as the results from the rainy days index are almost identical and this index assesses all rainy days between June and October. Kiremt rains in these years simply ended earlier and lasted much shorter than in the later decades. Together with the outlier in 1984, this explains the lower mean duration and higher variability in the 1980s.

The timing of kiremt has hardly changed over the period of observation with the exception of the 1980s. The onset of kiremt occurs on average in the first week of July with standard deviations between one and two weeks. Since the 1990s, the cessation of kiremt is on average in the second week of September with standard deviations between four and 13 days. In the 1980s, kiremt ended considerably earlier, in mid-August, and the timing showed much higher variability than in the following decades.

5.1.5 Dry Spells

Belg

The dry spell indices capture the length of the longest dry spell (CDD), the average length of dry spells (avgdsl) and the number of all dry spell days (totdsl) during each season. Since the dry spell indices were calculated within the rainy seasons that were determined in the timing indices, the previously mentioned methodological problems will carry through into these indices, influencing results and especially CV.

The longest dry spell (CDD) during belg lasted on average between 14 and 17 days in the kebele using only belg and between 13 and 19 days in the kebeles using both rainy seasons for cropping. Variability of CDD was very high between CV=0.41 and CV=0.57. On average, the dry spells span between eight and eleven days (avgdsl) with very similar results for both kebele groups. Again, variability of average dry spell length is very high with CV between 0.27 and 0.58. CDD and avgdsl show similar developments. Logically, the longest dry spell tends to be longer than the average dry spell length. Considering that a dry spell in the beginning of belg of more than seven days can potentially destroy an entire harvest (Rosell and Holmer 2007), an average length between eight and eleven days already indicates potentially devastating outcomes. Of course, this is dependent on crop type and variety as well as the timing of the dry spells.

The total count of dry spell days during belg, i.e. all days within a dry period of three or more days, is between 36 and 51 days, which is very high considering there are only 120 days between February and May and the duration of belg ranged between 41 and 73 days on average. This is emblematic of the issues with onset and cessation determination and suggests a very high variability of belg rains in terms of timing and distribution. Variability of the total dry spell length is also high with CV between 0.39 and 0.82. In the kebele using only belg for cropping, this variability has increased consistently since the 1990s from CV=0.59 to CV=0.82. There are no statistically significant trends over time in any of the three dry spell indices for belg rains.

Kiremt

Contrary to the results for belg, dry spells during kiremt were much shorter. The longest dry spell (CDD) lasted on average between seven and ten days. In the kebeles using both cropping seasons, the CDD in the 1980s and 1990s was one to two days longer than in the kebeles using only kiremt. While the two kebele groups experienced almost identical CDD in the 2000s, the kebeles using both seasons experienced, again, slightly longer CDD in the 2010s with about a 0.5-day difference. Variability for CDD is high throughout all timesteps and kebele groups, between CV=0.3 and CV=0.88. The highest variability was observed in the 2010s in both kebele groups.

The average dry spell length is not only almost identical for both kebele groups, but also almost identical throughout all timesteps, ranging from 5.4 to 6.5 days. Variability ranges between CV=0.27 to CV=0.37 in the first three timesteps. In the kebeles using belg and kiremt for cropping, variability of average dry spell length has consistently increased since the 1990s. In the 2010s, however, variability is at CV=0.64 in kebeles using only kiremt for cropping and at CV=0.43 in kebeles using both cropping seasons. This peak in the last timestep may be caused by the lower amount of datapoints, as this step is only seven years compared to the ten years in the other timesteps.

Total dry spell length ranges from 13.7 to 23.8 days in the kebeles using only kiremt and between 19.1 and 25.7 in the other kebele group. The higher total dry spell length in the kebeles using both cropping seasons is consistent with the higher CDD in this kebele group. This indicates, that these kebeles may be more affected by dry spells during kiremt. Variability of total dry spell length is the highest of all dry spell indices, ranging from CV=0.33 to CV=0.7. In both kebele groups, variability of total dry spell length has decreased over time. There are no statistically significant trends for either dry spell index during kiremt.

Compared to the dry spell indices for belg, kiremt is less affected by dry spells. Kiremt rain is more contiguous, which is evident when the dry spell indices are compared. Additionally, methodological issues come into play when rain is weaker overall, especially in drought years. No statistically significant trends over time were found for any dry spell index. All dry spell indices across all rainy seasons, kebele groups and timesteps showed very high variability. Increasing variability since the 1990s could only be observed in total dry spell length during belg in kebeles using only belg and in average dry spell length during kiremt in kebeles using both cropping seasons.

5.1.6 Extreme Events and Intensity

Belg

Extreme events and intensity indices include the maximum 1-day precipitation (Rx1day), extremely wet days (R99p), very wet days (R95p) and Simple Daily Intensity Index (SDII). During belg, Rx1day is similar for both kebele groups that use this season for cropping, ranging between 40.6 mm and 51 mm. CV of Rx1day in the BK kebeles is between 0.16 and 0.29, while the BO kebele shows far greater variability between 0.25 and 0.48. This means, while the heaviest rainfall events of the season are similarly intense in the two kebele groups, their intensity is far more variable in the kebele using only belg.

R99p shows the percentage of extremely wet days, i.e. the 1% wettest days during the entire period of observation, that occurred seasonally in the respective time step. It is an indicator for the frequency of heavy rainfall events. In both kebele groups using belg, one timestep showed none of these extremely wet days: the 2000s for BK kebeles and the 2010s for the BO kebele. CV could thus not be calculated for these timesteps. In the BO kebele, the percentage in the remaining timesteps was on average between 1.15% and 2.04%. In the BK kebeles, it ranged from 0.73% to 4.28%. A closer look into the data reveals, that the R99p index identified extremely wet days only in a handful of years, six years in the BO kebele and ten years in the BK kebeles. Since the mean, which is calculated here over ten (resp. seven) years, is not very robust against outliers, this can skew the data. It also explains extremely high CV values, up to 2.43. Such high variabilities should be interpreted extremely carefully. The most extreme rainfall events occur infrequently and there is no statistically significant trend over the period of observation.

R95p, the indicator for very wet days, captures the frequency of heavy rainfall events in a year. Other than R99p, it analyzes the 5% wettest days, which means more rainfall events are incorporated into the index overall. In the BO kebele, the frequency of very wet days was higher in the 1980s and 1990s at around 7.1%. In the later decades, it declined to around 4.7%. While the BK kebeles have also peaked in the 1990s at 8.4%, the frequency of very wet days was lower in the 1980s and has steadily declined since the 2000s to 4.8%. Variability of very wet days is very high, although not as high as variability of extremely wet days. CV ranges between 0.52 and 1.23. In the BO kebele, the frequency of very wet days has become more variable since the 1990s, although it was at its highest in the 1980s. Interestingly, the BK kebeles show the opposite development: CV has declined over the entire period of observation. This means, the frequency of very wet days during belg has declined in all kebele groups but in the BO kebele it has become more variable since the 1990s while it is less variable in the BK kebeles. There are no statistically significant trends in either extreme events index during belg.

Simple daily intensity index (SDII) measures the intensity of the rainfall. During belg, SDII is between 0.8 and 3.3 mm/day higher across all timesteps in the BK kebeles than in the BO kebele. Both groups experienced the most intense rainfall in the 1990s and a decline in SDII since. However, there are no statistically significant trends for SDII in either kebele group. Variability of SDII in the BO kebele has been the highest in the 1980s at CV=0.46 and has ranged between CV=0.2 and CV=0.25 in the following decades. In the BK kebeles, variability of SDII has peaked in the 1990s at CV=0.42 and also declined to around CV=0.22 since then. This means, the intensity of rainfall during belg used to be more variable than it is today.

Table 13 Results for the extreme events and intensity indices during kiremt including mean ($\bar{x}$), standard deviation (σ) and coefficient of variation (CV) for the kebele groups using kiremt for cropping (KO and BK).

			1981-1990	1991-2000	2001-2010	2011-2017
Rx1day	**KO**	$\bar{x}$	45.48	51.10	53.01	45.29
		σ	9.65	4.54	9.06	11.59
		CV	0.21	0.09	0.17	0.26
	BK	$\bar{x}$	57.04	55.53	50.85	47.08
		σ	11.27	9.55	10.14	15.19
		CV	0.20	0.17	0.20	0.32
R99p	**KO**	$\bar{x}$	0.96	1.46	1.14	1.16
		σ	1.88	1.34	1.18	2.26
		CV	1.96	0.92	1.03	1.94
	BK	$\bar{x}$	1.83	0.91	1.21	0.61
		σ	1.66	1.11	1.74	1.05
		CV	0.91	1.22	1.44	1.71
R95p	**KO**	$\bar{x}$	5.11	7.09	5.12	3.09
		σ	4.12	3.08	2.57	3.82
		CV	0.81	0.43	0.50	1.24
	BK	$\bar{x}$	8.44	5.78	4.17	3.56
		σ	7.04	3.21	2.25	4.74
		CV	0.83	0.56	0.54	1.33
SDII	**KO**	$\bar{x}$	16.07	17.75	17.06	16.42
		σ	4.59	1.30	1.72	3.08
		CV	0.29	0.07	0.10	0.19
	BK	$\bar{x}$	18.68	18.72	17.19	16.27
		σ	5.10	1.37	1.65	3.35
		CV	0.27	0.07	0.10	0.21

Kiremt

Results for the extreme events and intensity indices during kiremt can be found in table 13. The heaviest rainfall events of each year's kiremt season are on average not much more intense than during belg. Rx1day for kiremt ranges between 45.3 mm and 57 mm. In the KO kebeles, it was highest in the 1990s and 2000s. In the BK kebeles on the other hand, it has been declining since the 1980s. Although the Mann-Kendall test shows a declining trend for Rx1day in this kebele group, it is not statistically significant at the 95% confidence interval with a p-value of only 0.055 (table 14). Overall, the heaviest rainfall events during kiremt are more intense in the BK kebeles than in the KO kebeles. Both kebele groups show moderate CV of around 0.2 in the 1980s. After a decline in variability in the 1990s, it has been increasing since to as high as CV=0.32. Since the 1990s, Rx1day is more variable in the BK kebeles than in the KO kebeles. This means, the BK kebeles tend to receive more intense heavy rains at a higher variability during kiremt.

The most extreme rainfall events (R99p) during kiremt occur at a frequency between 0.61% and 1.83%. No statistically significant trends were observed over time. In the KO kebeles, CV

Table 14 Results of the Mann-Kendall trend test (tau) and Sen's slope estimator for the extreme events and intensity indices during kiremt for the two kebele groups using kiremt for cropping. Statistically significant trends at the 95% confidence interval (p < 0.05) are marked in bold font.

		tau	p	Sen's Slope
Rx1day	BK	-0.2222	0.0545	-0.3576
	KO	0.0871	0.4560	0.1243
R99p	BK	-0.1883	0.1313	0.0000
	KO	0.0349	0.7845	0.0000
R95p	**BK**	**-0.2926**	**0.0115**	**-0.1429**
	KO	-0.0918	0.4325	-0.0423
SDII	BK	-0.2162	0.0614	-0.0829
	KO	-0.0420	0.7240	-0.0106

of R99p was, like Rx1day, the highest in the 1980s at 1.96, has decreased in the 1990s and has been increasing again since then back to a very high variability of CV=1.94. In the BK kebeles, variability has been steadily increasing since the 1980s from CV=0.91 to CV=1.71 in the 2010s. Although the variability of R99p during kiremt is not quite as high as during belg, they should still be interpreted carefully.

The frequency of very wet days (R95p) during kiremt ranges from 3.56 to 8.44%. In the KO kebeles, it has been the highest in the 1990s and has decreased ever since. In the BK kebeles, R95p has been decreasing since the 1980s. This negative trend in the BK kebeles is statistically significant at the 95% confidence interval (table 14). Variability of very wet days in the KO kebeles has steadily increased since the 1990s from CV=0.43 to CV=1.24 in a similar manner as the previously discussed extreme events indices have. Although this development is similar in the BK kebeles, variability of R95p has been stagnating in the 1990s and 2000s. Overall, the frequency of very wet days has declined over the period of observation with a significant decline in the BK kebeles. Variability however has increased since the 1990s, with a consistent increase in the KO kebeles.

SDII has been stagnating in the KO kebeles between 16.07 and 17.75 mm/day throughout the period of observation. In the BK kebeles, rainfall intensity has decreased since the 1990s from 18.72 to 16.27 mm/day. The decrease is, however, not statistically significant at the 95% confidence interval. The BK kebeles used to receive more intense rainfall in the 1980s and 1990s than the KO kebeles, but this is no longer the case in the more recent time periods. Variability has, as was the case with most other extreme events indices for kiremt, been high in the 1980s, low in the 1990s and increasing since.

Throughout all but one (R95p in the BK kebeles) extreme events and intensity indices, variability during kiremt has increased consistently since the 1990s. In the 1980s, they all show high variability. This pattern of the 1980s kiremt seasons differing from the following decades has been consistent throughout this rainfall analysis. The 1980s were very unusual in terms of rainfall, with multiple severe droughts and highly variable kiremt rains.

5.2 Interview Analysis

5.2.1 Belg Only Kebele

In the kebele using only belg for cropping, problematic changes in rainfall are perceived by all respondents. The changes concern mainly the timing of the rain, in particular its onset: it is perceived as coming later and being increasingly unpredictable. Respondents view this as the biggest risk to their livelihood and are extremely concerned about the uncertainty of belg. Heavy rainfall is not a major issue in this kebele, mainly because the heavy rainfall events occur primarily during kiremt. As slopes are very steep in this kebele and due to unsuitable soil conditions, farmers do not use kiremt for cropping.

Most respondents view changes in yield as a direct result of changes in rainfall, i.e. good rainfall means high yields and poor rainfall means low yields. The respondents see the decline and the unpredictability of rainfall as the principal cause for decreasing yields. Livestock is an important, for some households even the only asset and respondents perceive a decline in livestock numbers partially as a result of changing rainfall. In a year with sufficient rainfall, there is enough fodder to feed existing livestock and potentially enough income from crop sale to increase herd sizes. In years with unfavorable rainfall conditions, it is possible to lose livestock to starvation due to fodder shortages, but most importantly, livestock is seen as an asset to generate income to compensate for low yields.

Livestock sale if often mentioned as the most important strategy to overcome food shortages: Farmers first sell offspring, particularly of goats and sheep, and will in case of severe shortages sell other livestock such as cows or ox. An ox is vital for the household’s agricultural activities and its loss can have catastrophic consequences, as it can prevent the household from achieving previously generated yields in the following cropping seasons. Another often mentioned strategy to overcome shortages is receiving support from the government or friends and relatives.

Respondents also mention a number of changes in agricultural practices due to the changing rainfall. Farmers mention that their ploughing frequency has increased to improve water percolation. Some respondents also mention a change from black to white barley as it is better in taste and better suited for drier conditions. Wealthier respondents use improved livestock breeds and eucalyptus is grown for building material, firewood and sometimes for sale. In case of insufficient rainfall, some households rely heavier on home gardens with irrigation. A number of other changes in agricultural practices are not exclusively seen as a reaction to changing rainfall, but rather to soil erosion and decreasing soil fertility. Strategies include terracing, check dams to prevent gullies, the use of fertilizer or compost.

5.2.2 Belg and Kiremt Kebeles

In the kebeles using both seasons for cropping, some farmers have access to irrigation systems, which greatly influences their water availability. They are concerned about the onset of belg and its increasing uncertainty. The onset has moved later in the year and it is increasingly difficult to know when the rain starts. Belg amounts are also perceived to have declined. Respondents perceive less rainfall overall, less intense rainfall and higher variability during belg. Belg scarcity is seen as one of the biggest threats to their livelihoods by farmers without access to irrigation. Farmers with access to irrigation, especially from the lowest-altitude kebele of Teikake, mention that using belg would not be possible without this access. In case of insufficient rainfall, the irrigation water or the second rainy season are used for compensation. Some respondents harvest twice a year, after each rainy season, while others harvest only once per year, i.e. sowing in belg and harvesting after kiremt. This is also dependent on the crops they grow.

Perceptions of changes in kiremt are much more heterogenous in these kebeles: not all interviewees perceive changes in kiremt rains. Those who do are especially concerned with the timing of the rain and mention later onset and earlier cessation of the rain. Decreasing amounts of kiremt rain is only mentioned by few respondents, while others negate decreasing amounts. Heavy rainfall events during kiremt are not seen as a major problem, although some mention it to be increasing. According to those farmers, it produces gullies, destroys terraces and leads to water logging and flooded fields. This is particularly mentioned by farmers in Teikake, where the recent construction of a railway prevents the water from draining off.

Lower yields and increasing food insecurity or the need to purchase food crops they used to be able to grow, are mentioned frequently by interviewees as the impacts they experience from changing rainfall. The main reason for this development is considered belg scarcity. Only few respondents mention other reasons such as soil erosion as the cause of declining yields. The respondents who are concerned with the timing of the rain mention it impacting the growing period: when belg is late, they sow later and crops are not fully mature to harvest before the heavier kiremt rains start, which potentially destroy the crops. When kiremt rain starts late, the crop is not fully matured by the time frost starts in October or November. This results in yields being lower than expected or the use of immature crops for fodder, meaning food crops need to be purchased. Overall, the access to irrigation is extremely important to these kebeles as the impacts of changing rainfall are primarily felt by farmers without this access.

As explained before, livestock sale is a frequent strategy used to overcome food shortages, as well as loans and support from the government or friends and relatives. Other than in the kebele groups using only one rainy season for cropping, farmers in these kebeles are able to compensate potential losses with the harvest from the other cropping season. Depending on the onset of the rain, farmers decide on the crops they grow and whether they compensate a potentially lost belg harvest with the kiremt harvest or vice versa. As in the kebele using only belg, eucalyptus trees are used as an important strategy to overcome food shortages. Other than in the previous kebele group, this is not limited to the sale of the trees, but also through providing labor by cutting and transporting them. Also, changes in crop types and varieties such as the use of more drought resistant or faster growing crops as well as frequent ploughing are mentioned strategies. The need for new crop varieties is mentioned as a direct consequence of decreasing rainfall amounts and changed timing.

5.2.3 Kiremt Only Kebeles

The most frequently mentioned problems regarding rainfall in the KO kebeles concern timing, i.e. duration, onset and offset of kiremt. Many respondents mention later onsets, increasing unpredictability and especially earlier cessation of the rain as a major problem. Often, respondents did not distinguish between changes in timing and changes in amounts of rain, i.e. shorter rainy periods also mean less rain overall. When asked about heavy rainfall, the answers are very heterogenous. Some mention increasing and others decreasing heavy rain events, however when it comes to impacts (e.g. top soil erosion, debris flow, gullies), respondents report an increase.

The perceived shorter rainy seasons, in particular the earlier cessation, lead to shorter growing periods, i.e. immaturity of the crops at the end of the season and a decline in yields. Respondents mention increasing food insecurity as a consequence, often the immature crops are used as fodder and food crops need to be purchased. Since a later onset of the rain means later sowing, many respondents have problems with their immature crops being affected by frost in October/November. Early cessation of the rain is often mentioned as a problem in combination with fertilizer usage, as the fertilizer leads to crop burn in case of a lack of rainfall.

The impacts of heavy rainfall events are mentioned frequently, top soil and gully erosion as well as seeds being washed away by heavy rainfall leading to a decline in or even a complete loss of yields. As mentioned above, this was not always seen as a result of changing rainfall, but of changing conditions on the ground such as a decline in vegetation cover on hillsides used for grazing. Farmers also report that they stopped fallowing their fields, for example after a drought or after land redistribution and took up ploughing activities instead. Heavy rainfall is considered a more severe problem as the frequently ploughed soil is more likely to be washed away.

5.2.4 Beyond Rainfall

Although changing rainfall is considered to be the primary driver of a decline in their quality of life by many respondents, other hardships are mentioned frequently. Problems surrounding soil such as soil erosion, formation of gullies, a decline in soil fertility and soil salinization are not always seen as results of changing rainfall by interviewees. Frost, weeds, pests and diseases to livestock and crops are putting further pressure on farmers' agricultural livelihoods. Weed infestation often led farmers to change crops. The most affected crop by the weeds is bean, which was often replaced by wheat or teff.

Land degradation and land scarcity are mentioned frequently, often in combination with declining livestock numbers due to a lack of grazing land. Farmers mention insecure tenure and a lack of land as the reasons why they stopped fallowing and intensified their agriculture through more frequent ploughing or fertilizer use. This led to a decline in soil fertility and lower yields. A range of agricultural strategies are applied to mitigate the effects of land degradation, for example terracing or fertilizer usage. The most frequently mentioned strategies to overcome food shortages, rainfall induced or otherwise, are livestock sale and government support. Additionally, it has become increasingly popular to sell local beer or liquor. Many respondents have begun diversifying their livelihoods in this way and others are considering it.

5.2.5 Causes

Only very few respondents commented on what they thought was causing the changing rainfall they perceived. Those who did talk about the causes of the rainfall changes referred to god and few respondents mentioned climate change as the cause. Most interviewees, however, said they did not know what caused the changes in rainfall. The respondents conveyed a feeling of helplessness in tackling the problem since the causes are either unknown to them or beyond their powers.

6 Discussion

Analyzing rainfall in a study area with high spatial variability was possible at the local level through CHIRPS. Issues such as missing or erroneous data, as is common with gauge data, proved challenging for comparison between observed and perceived environmental change in the past (De Longueville et al. 2020; Dickinson et al. 2017), did not arise. Even though satellite products tend to perform poorly over mountainous terrain, CHIRPS has been found to do well in the Ethiopian highlands (Ayehu et al. 2018; Dinku et al. 2018). However, as Gebrechorkos et al. (2018) pointed out, CHIRPS tends to perform better at lower temporal resolutions and this study cannot account for potential errors in the CHIRPS data. Concordance between CHIRPS and station data was improved through area averages (Gebrechorkos et al. 2018), thus using the median of several grid cell values per kebele should have improved the quality of the estimates.

The methods that were used in the rainfall analysis made a very comprehensive overview of rainfall in South Wollo possible, although a few adjustments had to be made in the analysis

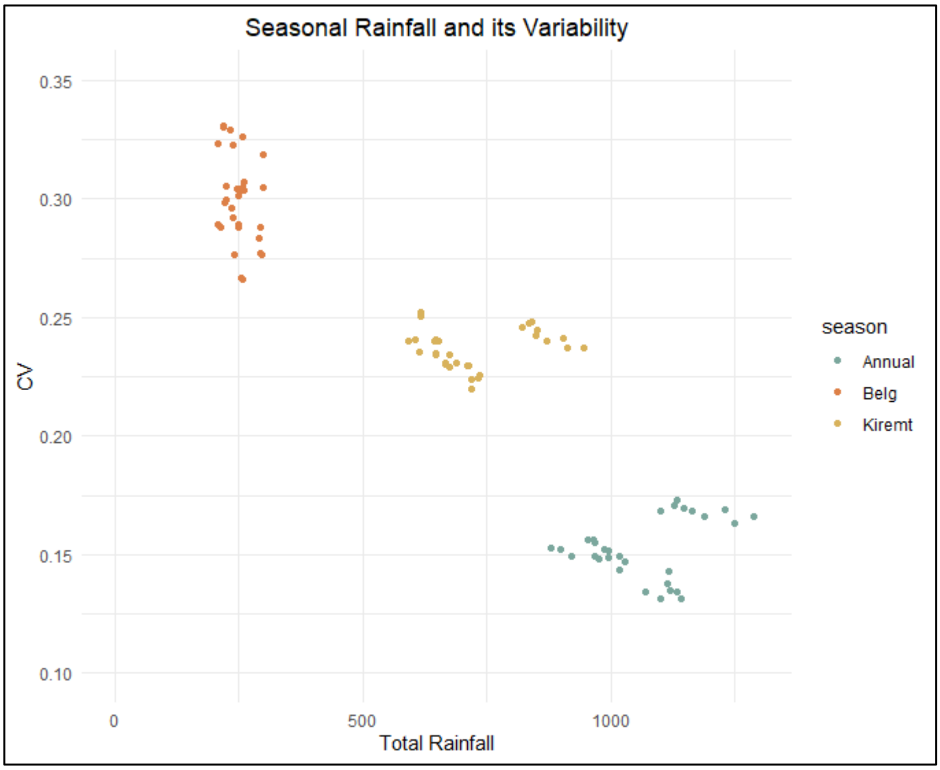

Figure 12 Mean seasonal and annual rainfall and its coefficient of variation (CV) in the study area between 1981 and 2017. Each dot represents one CHIRPS grid cell fully or partially within one of the study kebeles.

process. The contiguous time series data facilitated the determination of central concepts in farmers' perceptions such as the timing of the rainy seasons. However, it was necessary to work with two different definitions of the rainy seasons, one based on the determined onset and cessation of the season and one based on the months when these seasons generally occur. The reason for the application of the second definition were difficulties in determining the cessation of the rainy seasons, in particular in very dry years and for the lighter belg rains.

The high variability of belg rain compared to kiremt and annual rainfall (Alemu and Bawoke 2019; Mekonen and Berlie 2020; Rosell 2011) has been confirmed through the rainfall analysis (figure 12). While belg shows CV values between 0.26 and 0.33, CV for kiremt ranges mostly between 0.22 and 0.25. Annual rainfall shows the lowest variability at less than CV=0.18. The SRA evaluation has shown, that belg and kiremt behave differently. The geophysical processes influencing the rains, for example ENSO, can cause opposite developments in the rainy seasons (Fekadu 2015; Seleshi and Demaree 1995). The interview analysis has also shown that not all farmers are equally affected by rainfall changes in one of the two seasons. Changes at the annual level have little explanatory value and the need for seasonal rainfall evaluation in the Ethiopian highlands, especially when perceived changes are also assessed, is confirmed (Cochrane et al. 2020). The farmers in South Wollo perceive rainfall primarily in the way it affects their cropping activities and crop failure is the most prominently mentioned impact of deteriorating rainfall conditions. Also, temperatures were reported to have increased in the study area (Asfaw et al. 2018; Mekonnen et al. 2018) which may have caused higher evapotranspiration and thus lower water availability (Osbahr et al. 2011). Rainfall changes were the most frequently mentioned threat to the farmers livelihoods, especially with regard to onset, duration and cessation of the rain. This is mentioned frequently in the literature and emphasizes the importance of assessing timing and distribution of rainfall instead of aggregate amounts in drought monitoring (Below et al. 2015; Cochrane et al. 2020; Simelton et al. 2013). Future studies can consider emphasizing staple crops, their growing period and water needs when comparing meteorological observations and perceived rainfall change (Rosell and Holmer 2007).

Determination of the timing of the rainy seasons proved difficult in the study area and the most appropriate method to capture the rainy seasons was explored in this study. Although the timing is a frequently mentioned crucial factor in the literature (Asfaw et al. 2018; Mekonnen et al. 2018), few studies have comprehensively assessed it with the inclusion of perception data so far. Particularly the cessation of the rainy seasons has hardly been explored in this context. Considering the focus on farmers' perceptions, the approach with a threshold-based onset definition and an anomaly-based cessation definition was the most expedient in this study. Only in a few years, the onset and offset determination of the rainy seasons produced unsatisfactory results such as rainy season durations of less than five days, which mainly concerned drought years. However, working with the rainy seasons determined through onset and cessation calculations for all indices would have led to several errors in the analysis as is evident in the results for duration and dry spells.

For example, since the belg season in 1999 was determined through a singular rainfall event, of course, no dry spells could be found in that year. As the results for SRA showed, belg rains in 1999 were almost completely absent. When looking at the total rainfall and rainy days index for this year, for example in the BO kebele, the total rainfall between February and May was 95 mm falling over the course of nine days, a third of which can be attributed to the single event that determined the onset. The remainder of the season was characterized by singular, less intense rainfall events with seven or eight, sometimes even more than 20 dry days in between. These dry spells are not captured in the results since cessation was determined before the isolated rainfall events occurred. While this is certainly an extreme example, it illustrates quite well that the results of the duration and dry spell indices must be interpreted in the context of the other indices.

Another possible way the duration and dry spell indices can be influenced through the onset and offset determination is the problem of early onsets through the threshold method (figure 7). For example, in the year 1983, the BO kebele received a lot of rain in belg. During two days in late February, it rained about 20 mm which was determined as the onset of the rainy season

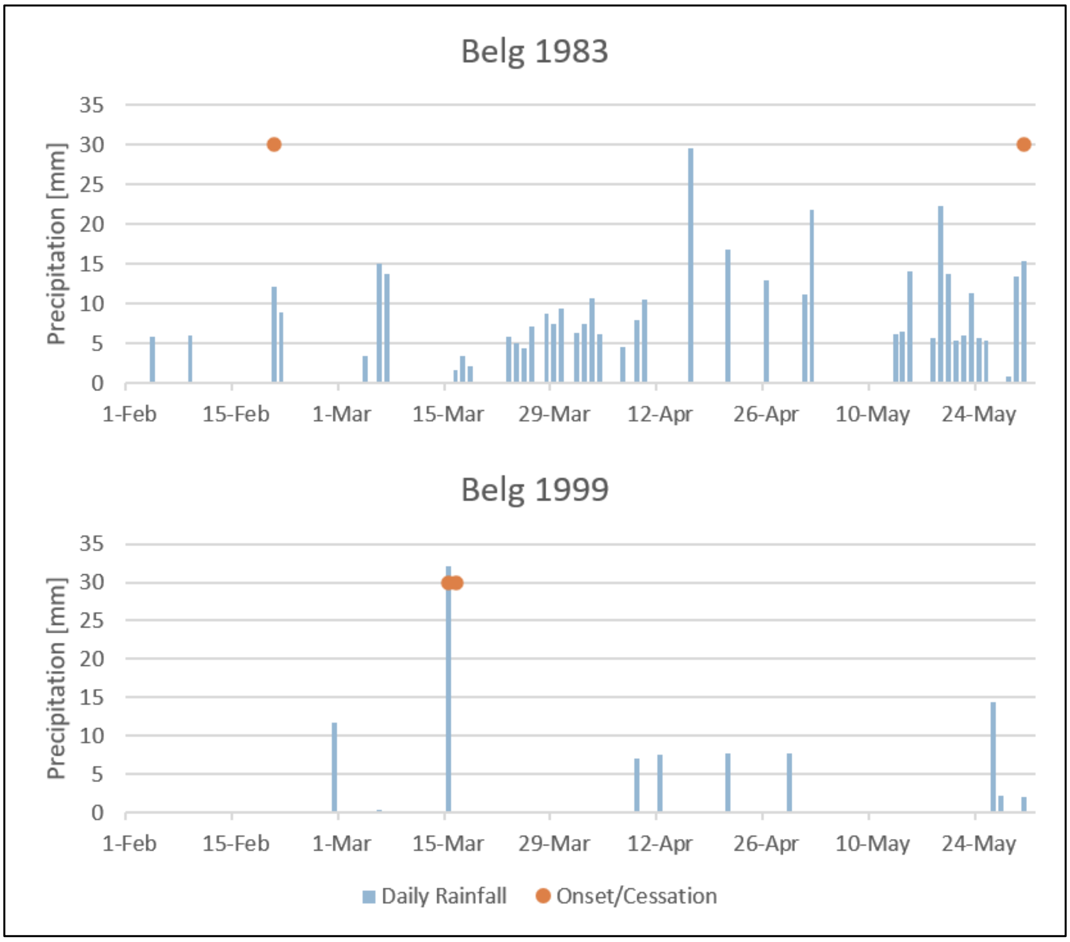

Figure 13 Belg season in a wet and a dry example year in the kebele using only belg (Adej) for cropping. Orange dots symbolize the determined onset and cessation of the rainy season.

through the threshold method. Until late March, the kebele received another 39 mm of rain during two rainfall events lasting two to four days with eight and ten dry days in between the respective rainfall events. Only then, the area received consistent rainfall of 102 mm over a period of about three weeks. Until mid-May, there were again several isolated rainy days with four to ten dry days in between and in the last 19 days of May, the area received another 131 mm of consistent rainfall. Only after that, the cessation of belg was determined by the calculation.

For the dry spell indices, this results in a quite high number of total dry spell days which should be interpreted in the context of a very long, very wet rainy season and the results of the average dry spell length and CDD. To illustrate the difference between these example years, the belg season including the determined onset and offset calculations are illustrated in figure 13. Particularly the extreme events and intensity indices, which are not primarily influenced by or dependent on the timing of the seasons, benefited from using the monthly rainy season definition. The difficult onset and offset determination for belg was also mirrored in the interview data: respondents reported a complete failure of belg rains in some years. These years could be identified through the SRA results and they also proved to be the years where the determined belg onset and offset were within a week from each other.

The Mann-Kendall trend test was performed for two annual indices and twelve seasonal indices for the respective kebele groups. Altogether, the results from the MK test include 54 trend analyses. Only seven showed statistically significant trends at the 95% confidence interval. Figure 14 shows a summary of all statistically significant trends and increasing variabilities in contrast with a simplified version of farmers' perceptions.

The kebele using only belg for cropping is affected by the increasingly late onset of the rain and less rainfall overall. The onset of belg has moved from mid to late February into mid-March

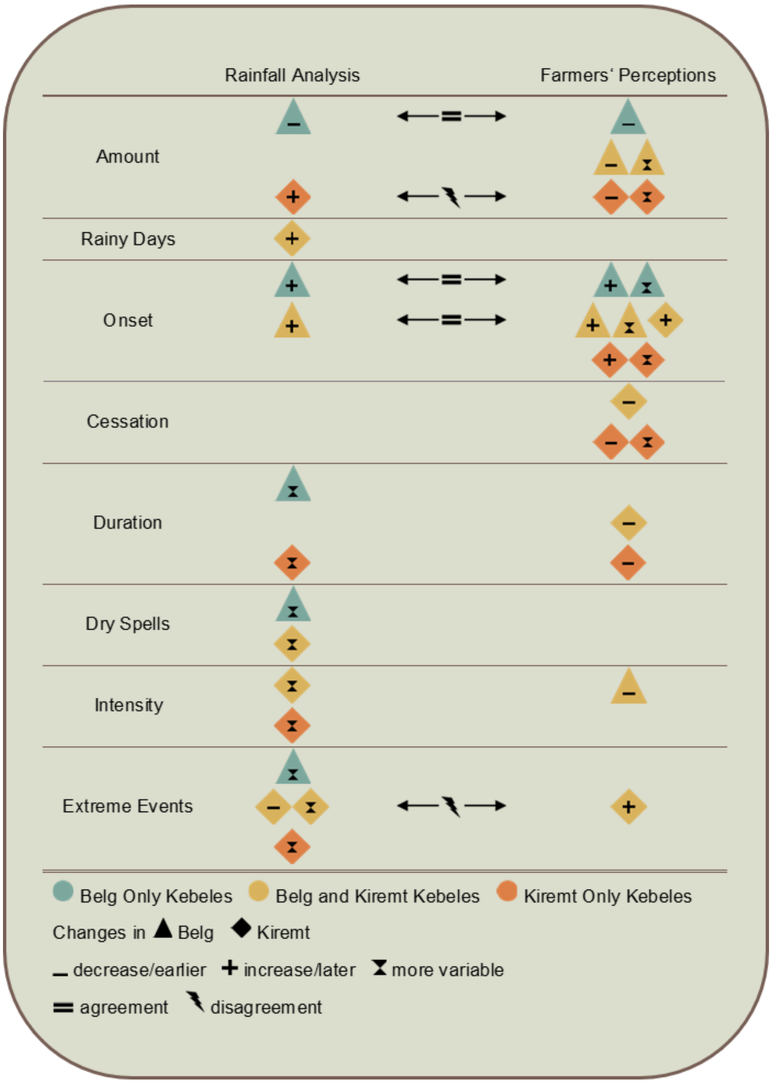

Figure 14 Summary of the results. Dry spells include CDD, avgdsl and totdsl. Extreme events include Rx1day, R95p and R99p. The indicator for intensity is SDII. Rainfall indicators were marked as increasing or decreasing when there was a statistically significant trend at the 95% confidence interval found in the MK test. Rainfall indicators were marked as more variable when CV consistently increased in at least the three timesteps since 1991. For dry spells and extreme events, this is considered true when it is true for one index in the respective category. Farmers' perceptions were coded as more variable when the indicator was described as "unpredictable" or "increasingly uncertain", when answers on an indicator were contradictory in a kebele group, they do not appear in this figure.

over the 37 years observed. These results are consistent with the literature, as the later onset and decreasing amounts of belg rain were previously observed in the study area (Alemayehu and Bewket 2017; Mekonen and Berlie 2020; Rosell 2011). The results from the interview analysis reflect these changes: farmers perceived belg to start later, to be increasingly unpredictable and rainfall amounts to be declining. Unpredictability was coded as increasing variability, which was often mentioned in the context of belg onset. Although the onset has been very variable throughout the study period, CV values have decreased since the 1990s. CV has also decreased for rainfall amounts. When respondents mention unpredictability, this could also be reflected in the later onset of the rain since farmers' agricultural decisions depend on the timing of the rain and the changing onset will certainly affect the respondent's cropping schedule. When looking at the rainfall indices, where variability has increased since the 1990s, only three out of twelve concern the BO kebele (figure 15). They are total dry spell length, belg duration and the frequency of very wet days (R95p). CV and standard deviations for the extreme events indices R95p and R99p are extremely high and should be interpreted with care as they might just be statistical noise. Since duration and total dry spell length rely on the

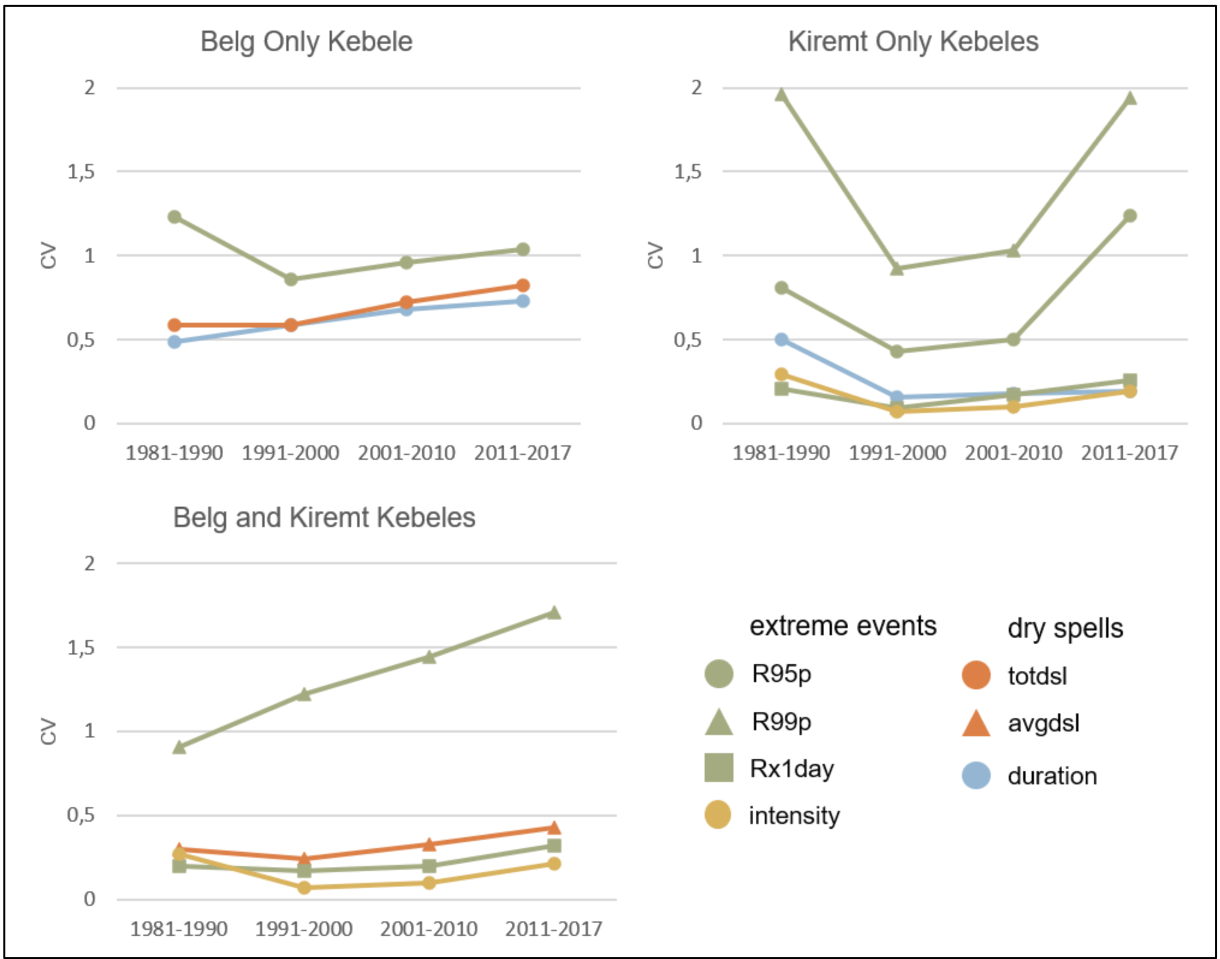

Figure 15 All indices where coefficient of variation (CV) has increased at least since the 1990s for each kebele group. In the BK kebeles, all increases in CV have been observed for kiremt rainfall. Dry spells include avgdsl and totdsl. Extreme events include Rx1day, R95p and R99p.

calculated onset and cessation dates and there were more dry belg years since the 1990s, as the SRA results have shown, the increase in variability in these two indices might be caused by methodological issues rather than an actual increase. Thus, it is possible, that belg rains, although they have always been highly variable, have not experienced an increase in variability.

The later onset of belg will certainly delay the growing period. As a result, the farmers reported crops being immature by the time the stronger kiremt rains start. At the high altitude and steep slopes in this part of the study area, the strong rains can lead to crop loss through erosion or hail (Groth et al. 2020; Hermans and Garbe 2019). The perception of increasingly uncertain rainfall may also be expressed in the increasing variability of belg duration and the total dry spell length. Belg-dependent farmers have previously been identified as very vulnerable to changing rainfall (Rosell 2011) and limited irrigation access exacerbates this problem. The interview data and Hermans and Garbe (2019) showed that these farmers are very dependent on livestock-sale to generate income in case of a failed harvest. This high dependency on livestock results in an increased vulnerability to falls in prices. During the 2015 drought, decreasing livestock prices were reported in the study area (Menghistu et al. 2018). This will put further pressure on the farmers' livelihoods.

The kebeles using both cropping seasons are also affected by the later onset of belg as the trend analysis has shown. The increase in rainy days in annual data and seasonally for kiremt describes the same development. Although not statistically significant at the 95% confidence interval, rainfall amounts during kiremt have declined since the 1990s and so has rainfall intensity (SDII), i.e. there is less rainfall spread over more rainy days. The 1980s were an exceptionally dry period for kiremt rains and may lead to distortions in the statistics (Bewket and Conway 2007). The frequency of very wet days occurring in these kebeles has also declined over the period of observation. In these kebeles, rainfall has become less, but not significantly less intense and heavy rainfall events have become less frequent during kiremt. Increasing variability was only observed in kiremt indices (figure 15). The average length of dry spells has become more variable. Although dry spells are not mentioned frequently by respondents, an earlier cessation of kiremt rains is. The MK test results have shown that the end of kiremt is later, although not significantly later. Considering the 1980s are an outlier in the rainfall analysis, the cessation of kiremt can be described as largely stable. The increasing variability of average dry spell length may be expressed in the perception of earlier cessation since farmers may equate crop failure as a result of dry spells with the cessation of rainfall. All other indices with increasing variability since the 1990s in this kebele group concern extreme events and intensity: R99p, Rx1day and SDII. R95p in this kebele group shows a statistically significant decrease and extreme event frequency and intensity have become more variable.

The perceived increase in extreme events may be expressed in the increasing variability of these rainfall indices.

Farmers in these kebeles had the least dire perception of their current quality of life. The kebeles using belg and kiremt for cropping are also those where some farmers have access to irrigation systems. Irrigation access has already been mentioned as shaping perceptions of rainfall change, since dependency on rainfall is reduced (Niles and Mueller 2016). It was evident in the interview data, that the farmers without irrigation access were very affected by the later belg onset, while those who were able to irrigate their fields mentioned that cropping during belg without irrigation would be impossible. The BK are identified as kebeles with low land degradation (table 1). That and the irrigation access considered, it is possible that farmers in these kebeles have it easier to mitigate the effects of changing rainfall. There is also the possibility of compensating a failed harvest in one season with the harvest of the other, as was mentioned by some respondents. Thus, they perceive their overall situation as better than farmers in the other kebele groups.

In the kebeles using only kiremt for cropping, the only statistically significant trend shown in the MK test was increasing rainfall amounts during kiremt. According to Sen's slope estimator, these kebeles received 6.17 mm more rain every year. Interestingly, farmers perceived the opposite phenomenon: they felt it had been raining less. The severe drought in 2015 may have influenced this perception, since extreme and more recent events have been shown to be extraordinarily relevant in shaping people's perception of environmental change (Debela et al. 2015; Simelton et al. 2013). However, as SRA results showed, the two years between the drought and data collection were some of the wettest years in the period of observation.

In the KO kebeles, the most variability increases since the 1990s have occurred (figure 15). The duration of kiremt has become more variable. Farmers in this kebele group perceived a shorter rainy season, particularly due to earlier cessation of kiremt. While this could not be confirmed through the rainfall analysis, the increasingly variable duration of the season may be expressed in this perception. Farmers dependent on rainfed agriculture rely on relatively stable and predictable rainfall patterns in their decision-making process (MacLeod 2018; Simelton et al. 2013). Thus, more variable rainy season duration can affect farmers' perception of the season.

The other indices showing increasing variability in the last 27 years of the period of observation are all concerned with extreme events and rainfall intensity: R99p, R95p, Rx1day and SDII, i.e. rainfall intensity and the intensity and frequency of extreme events have become more variable. However, due to some extremely high CV values, these developments may simply show statistical noise. Farmers in these kebeles gave heterogenous answers regarding the development of extreme events in their villages. There was agreement regarding the negative impacts of heavy rainfall events, e.g. soil erosion or gully formation, becoming more severe. The increasingly variable frequency and intensity of extreme events may be expressed in some respondents' perceptions, however, the overall picture is very heterogenous. As Adimassu et al. (2014) have previously pointed out, although rainfall may have increased, deteriorating soil conditions can be exacerbated by droughts, raising variability in crop production despite higher inputs and stagnating productivity. Also, the interview data suggests, that the impacts of heavy rainfall events have become more severe because of land degradation. While this study does not provide any information on the conditions of the soil, it is remarkable that two out of the three kiremt only kebeles were identified as areas with high land degradation in the site selection process (table 1). After all, increasing top soil or gully erosion also depends on land management and agricultural activities (Nyssen et al. 2004) and this study is unable to provide information on the change in quality of the soil.

Overall, the interview analysis posed a great challenge, since some respondents did not separate between phenomena that were assessed separately in the rainfall analysis, e.g. equating shorter rainy seasons with less rain. Other aspects, for example dry spells and rainy days, were almost never mentioned in the interviews. As a result, some changes in rainfall perceived by local farmers may be expressed in different indices in the rainfall analysis. The importance of different climate reference scales used by farmers and through meteorological analysis is evident (Debela et al. 2015; Howe et al. 2014). Also, the concept of rainfall variability may be difficult to understand for farmers and would require a more detailed explanation in order to collect robust perception data (Madhuri and Sharma 2020).

Narratives about changing rainfall in local communities can manifest potentially inaccurate perceptions of change. International aid organizations, extension workers and political institutions in the area focus strongly on abnormal rainfall and extraordinary drought (Meze-Hausken 2004). As rainfall is largely seen as something that cannot be influenced locally, it is easier to point to it as the cause of various agricultural problems rather than addressing highly conflict prone issues such as land degradation or land scarcity (Ege 2017). Soil erosion and land degradation are perceived as less of a risk than rainfall change by the small-scale farmers. There may be simplifying mechanisms leading to this perception: rainfall is perceived as the cause of declining yields as farmers are unable to capture the complexity of the situation. Group dynamics, institutional, psychological, social and cultural processes can amplify this perception (Kasperson et al. 1988). However, it is difficult to assess these developments through a language barrier (Marx et al. 2007; Roncoli 2006).

7 Conclusions

Rainfall variability and rainfall trends in six kebeles in South Wollo were analyzed at the local level using CHIRPS. The high spatial and temporal resolution of the dataset made a detailed assessment of different aspects of rainfall in the study area possible. During the lighter belg season, rainfall is far more variable, both in terms of timing and amounts, than during the main rainy season in the summer months.

The major changes in rainfall in the study area between 1981 and 2017 are

(1) the increasingly late onset and lower rainfall amounts during belg,

(2) the increasing rainfall amounts in kiremt in the kebeles using only kiremt for cropping,

(3) the increasing number of rainy days and decreasing frequency of heavy rainfall events in the kebeles using both cropping seasons and

(4) increasingly variable intensity and frequency of extreme events and intensity of rainfall during kiremt.

For the small rainy season, these results are largely consistent with small scale farmers' perception of rainfall. For kiremt rains, farmers perceived mainly changes in the timing of the rain, which was not evident from the rainfall analysis. The perceived changes may be expressed in different metrics in the rainfall analysis such as the variability of dry spells. Other factors such as changes in soil fertility, increasing population or changing needs for water may also come into play. Rainfall amounts are not the primary indicator for rainfall change as perceived by small-scale farmers. They perceive rainfall as it relates to their agricultural activities which are mainly determined by the timing and distribution of the rainfall. Confusion about planting dates can lead to crop loss and higher dependency on food aid.

When collecting data on perceptions of environmental change, different reference scales of climate indicators should be incorporated into survey design. Drought monitoring and forecasting as well as advice by extension workers or aid organizations should strongly focus on agricultural calendars and growing periods. A crop-specific assessment of rainfall needs is advisable when comparing meteorological data and farmers' perceptions.

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Annex

A Tables with mean ($\overline{x}$), standard deviation (σ) and coefficient of variation (CV) results. Indices where CV has increased since at least 1991 are marked in bold font.

Annual Indices

			1981-1990	1991-2000	2001-2010	2011-2017
RR	BO	$\overline{x}$	1148.38	1311.87	1198.55	1225.29
		σ	201.70	181.30	153.41	271.51
		CV	0.18	0.14	0.13	0.22
	BK	$\overline{x}$	1005.12	1140.91	1019.07	1042.72
		σ	155.50	123.79	105.72	201.79
		CV	0.15	0.11	0.10	0.19
	KO	$\overline{x}$	939.18	1084.57	987.57	1040.38
		σ	150.21	134.47	123.07	207.05
		CV	0.16	0.12	0.12	0.20
rd	BO	$\overline{x}$	73.60	69.00	67.10	76.00
		σ	20.55	9.45	9.01	9.40
		CV	0.28	0.14	0.13	0.12
	BK	$\overline{x}$	63.25	66.65	66.35	71.21
		σ	12.96	8.11	6.80	7.04
		CV	0.20	0.12	0.10	0.10
	KO	$\overline{x}$	69.40	69.90	66.90	71.43
		σ	15.02	6.55	9.30	7.48
		CV	0.22	0.09	0.14	0.10

Belg

			1981-1990	1991-2000	2001-2010	2011-2017
RR	BO	$\overline{x}$	301.01	243.34	214.53	227.71
		σ	80.84	88.12	67.69	59.14
		CV	0.27	0.36	0.32	0.26
	BK	$\overline{x}$	323.56	262.39	236.23	260.12
		σ	52.52	101.58	66.37	53.35
		CV	0.16	0.39	0.28	0.21
rd	BO	$\overline{x}$	22.40	15.30	14.10	17.29
		σ	10.71	5.87	2.69	3.86
		CV	0.48	0.38	0.19	0.22
	BK	$\overline{x}$	20.95	15.20	15.65	18.07
		σ	7.60	5.75	2.86	1.54
		CV	0.36	0.38	0.18	0.09
onset	BO	$\overline{x}$	52.00	60.90	57.20	76.43
		σ	13.70	18.77	12.88	15.31
		CV	0.26	0.31	0.23	0.20
	BK	$\overline{x}$	49.65	58.70	57.65	71.64
		σ	15.72	20.73	15.85	13.00
		CV	0.32	0.35	0.27	0.18
offset	BO	$\overline{x}$	111.60	115.20	102.70	116.29
		σ	32.18	23.73	27.18	25.10
		CV	0.29	0.21	0.26	0.22

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			1981-1990	1991-2000	2001-2010	2011-2017
offset	BK	x̄	121.90	106.45	105.60	125.93
		σ	22.79	30.83	21.55	20.92
		CV	0.19	0.29	0.20	0.17
dur	BO	x̄	60.60	55.30	46.50	40.86
		σ	29.79	32.49	31.48	29.66
		CV	**0.49**	**0.59**	**0.68**	**0.73**
	BK	x̄	73.25	48.75	48.95	55.29
		σ	22.43	36.49	24.86	23.68
		CV	0.31	0.75	0.51	0.43
cdd	BO	x̄	16.80	13.90	14.11	16.33
		σ	9.30	7.46	8.25	8.57
		CV	0.55	0.54	0.58	0.52
	BK	x̄	18.90	19.25	12.95	17.29
		σ	7.81	9.96	5.39	9.79
		CV	0.41	0.52	0.42	0.57
totdsl	BO	x̄	39.60	40.70	35.30	28.86
		σ	23.37	24.17	25.43	23.72
		CV	**0.59**	**0.59**	**0.72**	**0.82**
	BK	x̄	51.35	36.45	36.70	38.43
		σ	20.03	29.59	19.87	19.01
		CV	0.39	0.81	0.54	0.49
avgdsl	BO	x̄	8.24	10.64	10.00	9.73
		σ	3.42	6.13	6.67	5.27
		CV	0.41	0.58	0.67	0.54
	BK	x̄	9.42	10.06	7.91	9.87
		σ	3.10	3.56	2.11	5.07
		CV	0.33	0.35	0.27	0.51
Rx1day	BO	x̄	47.48	50.97	45.19	42.74
		σ	22.57	12.89	20.55	16.03
		CV	0.48	0.25	0.45	0.37
	BK	x̄	47.63	50.26	40.55	45.01
		σ	10.45	14.71	7.72	7.01
		CV	0.22	0.29	0.19	0.16
R99p	BO	x̄	2.04	1.27	1.15	0.00
		σ	4.95	2.83	2.44	0.00
		CV	2.43	2.23	2.12	---
	BK	x̄	1.49	4.28	0.00	0.73
		σ	2.46	6.48	0.00	1.25
		CV	1.65	1.51	---	1.71
R95p	BO	x̄	7.08	7.12	4.70	4.60
		σ	8.72	6.13	4.50	4.78
		CV	**1.23**	**0.86**	**0.96**	**1.04**
	BK	x̄	5.77	8.37	6.45	4.75
		σ	5.85	8.39	5.35	2.47
		CV	1.01	1.00	0.83	0.52
SDII	BO	x̄	15.96	16.16	15.02	13.50
		σ	7.34	3.88	3.07	3.34
		CV	0.46	0.24	0.20	0.25

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			1981-1990	1991-2000	2001-2010	2011-2017
	BK	x̄	17.14	19.41	15.80	14.73
		σ	4.94	8.24	3.62	3.25
		CV	0.29	0.42	0.23	0.22

Kiremt

			1981-1990	1991-2000	2001-2010	2011-2017
RR	KO	x̄	627.36	809.99	743.22	769.20
		σ	172.47	159.28	101.24	204.63
		CV	0.27	0.20	0.14	0.27
	BK	x̄	627.70	808.76	716.72	735.71
		σ	174.87	156.81	85.46	194.64
		CV	0.28	0.19	0.12	0.26
rd	BO	x̄	41.00	45.70	44.13	46.86
		σ	11.80	8.13	7.58	9.07
		CV	0.29	0.18	0.17	0.19
	BK	x̄	35.55	43.60	42.05	45.00
		σ	10.50	9.18	6.26	7.61
		CV	0.30	0.21	0.15	0.17
onset	KO	x̄	187.90	179.87	179.97	185.86
		σ	10.17	13.46	10.34	8.49
		CV	0.05	0.07	0.06	0.05
	BK	x̄	187.80	182.00	180.60	187.71
		σ	11.13	11.90	10.50	8.57
		CV	0.06	0.07	0.06	0.05
offset	KO	x̄	235.87	249.47	247.53	251.48
		σ	22.39	5.38	3.98	9.33
		CV	0.09	0.02	0.02	0.04
	BK	x̄	239.20	253.35	248.80	257.93
		σ	23.19	10.92	6.05	11.71
		CV	0.10	0.04	0.02	0.05
dur	KO	x̄	48.97	70.60	68.57	66.62
		σ	24.38	11.21	12.68	12.67
		CV	**0.50**	**0.16**	**0.18**	**0.19**
	BK	x̄	52.40	72.35	69.20	71.21
		σ	25.67	8.57	14.09	12.54
		CV	0.49	0.12	0.20	0.18
cdd	KO	x̄	6.85	7.63	10.07	7.86
		σ	2.09	4.05	6.25	4.05
		CV	0.30	0.53	0.62	0.51
	BK	x̄	7.67	9.70	10.10	8.43
		σ	4.90	4.94	8.87	4.00
		CV	0.64	0.51	0.88	0.48
totdsl	KO	x̄	13.73	23.80	21.27	17.71
		σ	9.58	15.35	11.83	7.85
		CV	0.70	0.65	0.56	0.44

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			1981-1990	1991-2000	2001-2010	2011-2017
	BK	x̄	19.10	25.70	21.55	21.71
		σ	12.40	14.87	12.64	7.21
		CV	0.65	0.58	0.59	0.33
avgdsl	KO	x̄	5.86	5.73	5.74	6.50
		σ	1.63	2.13	1.56	4.19
		CV	0.28	0.37	0.27	0.64
	BK	x̄	5.59	5.36	5.37	5.88
		σ	1.70	1.31	1.80	2.54
		CV	**0.30**	**0.24**	**0.33**	**0.43**
Rx1day	KO	x̄	45.48	51.10	53.01	45.29
		σ	9.65	4.54	9.06	11.59
		CV	**0.21**	**0.09**	**0.17**	**0.26**
	BK	x̄	57.04	55.53	50.85	47.08
		σ	11.27	9.55	10.14	15.19
		CV	**0.20**	**0.17**	**0.20**	**0.32**
R99p	KO	x̄	0.96	1.46	1.14	1.16
		σ	1.88	1.34	1.18	2.26
		CV	**1.96**	**0.92**	**1.03**	**1.94**
	BK	x̄	1.83	0.91	1.21	0.61
		σ	1.66	1.11	1.74	1.05
		CV	**0.91**	**1.22**	**1.44**	**1.71**
R95p	KO	x̄	5.11	7.09	5.12	3.09
		σ	4.12	3.08	2.57	3.82
		CV	**0.81**	**0.43**	**0.50**	**1.24**
	BK	x̄	8.44	5.78	4.17	3.56
		σ	7.04	3.21	2.25	4.74
		CV	0.83	0.56	0.54	1.33
SDII	KO	x̄	16.07	17.75	17.06	16.42
		σ	4.59	1.30	1.72	3.08
		CV	**0.29**	**0.07**	**0.10**	**0.19**
	BK	x̄	18.68	18.72	17.19	16.27
		σ	5.10	1.37	1.65	3.35
		CV	**0.27**	**0.07**	**0.10**	**0.21**

B Tables with results of the Mann-Kendall trend test with Kendall's tau (positive or negative trend), a two-sided p-value (hypothesis testing, significant trends at the 95% confidence interval are marked in bold font) and Sen's Slope estimator (change per unit time)

Annual Indices

		tau	p	Sen's Slope
RR	BO	0.1201	0.3015	2.5359
	BK	0.0390	0.7437	0.8466
	KO	0.1231	0.2894	3.0321
rd	BO	0.0530	0.6562	0.1188
	BK	**0.2293**	**0.0482**	**0.3333**
	KO	0.0332	0.7835	0.0423

Belg

		tau	p	Sen's Slope
RR	BO	**-0.2462**	**0.0330**	**-2.6589**
	BK	-0.2222	0.0545	-2.3490
rd	BO	-0.1249	0.2934	-0.0801
	BK	-0.0640	0.5911	-0.0359
onset	**BO**	**0.2736**	**0.0185**	**0.6883**
	BK	**0.2805**	**0.0155**	**0.5526**
offset	BO	-0.0136	0.9166	-0.0623
	BK	0.0030	0.9896	0.0000
dur	BO	-0.2121	0.0688	-0.7454
	BK	-0.1687	0.1464	-0.7670
cdd	BO	-0.0650	0.5983	-0.0625
	BK	-0.0903	0.4594	-0.0952
totdsl	BO	-0.1402	0.2287	-0.3586
	BK	-0.1293	0.2662	-0.4302
avgdsl	BO	-0.0153	0.9094	0.0000
	BK	-0.0411	0.7443	-0.0185
Rx1day	BO	-0.0270	0.8240	-0.0741
	BK	-0.1081	0.3531	-0.1647
R99p	BO	-0.0793	0.5664	0.0000
	BK	-0.1332	0.3136	0.0000
R95p	BO	-0.0592	0.6349	0.0000
	BK	0.0046	0.9791	0.0000
SDII	BO	-0.0360	0.7636	-0.0264
	BK	-0.1141	0.3266	-0.0675

Kiremt

		tau	p	Sen's Slope
RR	BK	0.2012	0.0819	4.4125
	KO	**0.2643**	**0.0221**	**6.1692**
rd	**BK**	**0.2384**	**0.0410**	**0.2981**
	KO	0.0995	0.3950	0.1350
onset	BK	-0.0182	0.8855	-0.0109
	KO	-0.0935	0.4247	-0.0976
offset	BK	0.2071	0.0750	0.2857
	KO	0.2155	0.0632	0.2546
dur	BK	0.1873	0.1074	0.3964
	KO	0.2078	0.0731	0.4452
cdd	BK	0.0258	0.8378	0.0000
	KO	0.0660	0.5850	0.0303
totdsl	BK	0.0469	0.6945	0.0590
	KO	0.0932	0.4249	0.1333
avgdsl	BK	0.0017	1.0000	0.0000
	KO	-0.0325	0.8004	-0.0022

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		tau	p	Sen’s Slope
Rx1day	BK	-0.2222	0.0545	-0.3576
	KO	0.0871	0.4560	0.1243
R99p	BK	-0.1883	0.1313	0.0000
	KO	0.0349	0.7845	0.0000
R95p	**BK**	**-0.2926**	**0.0115**	**-0.1429**
	KO	-0.0918	0.4325	-0.0423
SDII	BK	-0.2162	0.0614	-0.0829
	KO	-0.0420	0.7240	-0.0106

Erklärung

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Halle (Saale), den

Lena Hubertus