MULTIDECADAL RAINFALL VARIABILITY IN SAHEL

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Written by: Ellen Berntell
Supervisor: Qiong Zhang
Heiner Körnich
Léon Chafik
Abstract

The African Sahel is a water vulnerable region located in northern Africa. It exhibits strong inter-annual rainfall variability on several different time scales. During the 20th century the Sahel region experienced extended dry periods and severe droughts, with devastating effects on the livelihoods of the people in the region. In this study the multidecadal variability of Sahel precipitation is examined in the gridded observational dataset CRU and in the 20th-century reanalysis ERA20C. Additionally, we use the Hadley sea surface temperature and sea level pressure datasets. Our analysis of the Sahel (10°–18°N, 20°W -30°E) July-September rainfall observations using CRU shows a clear multidecadal variability with a dominating period of 60-80 years and a high correlation to the annual mean North Atlantic sea surface temperatures on a multidecadal scale. Using a global field correlation and a single value decomposition we could see that the highest correlation between low-pass filtered Sahel rainfall and sea surface temperatures was located along latitudinal bands in the mid-latitudes and in the sub-polar region as well as in eastern North Atlantic with values around $R = 0.8$. Similarly, ERA20C reanalysis dataset exhibits multidecadal rainfall variability in Sahel with a dominating period of 60-80 years, however largely out of phase with the observational dataset and with no correlation to the North Atlantic sea surface temperatures. The composite analysis of low-pass filtered data showed a clear increase of rainfall across Sahel in wet compared to dry years for both the CRU observational and ERA20C reanalysis datasets. The composite difference for the sea level pressure and surface temperature suggest that a strengthening of the thermally driven meridional pressure gradient between Sahara and the Coast of Guinea in wet compared to dry years is the driving mechanism for the multidecadal rainfall variability in Sahel for both the observational and reanalysis dataset. The strengthened temperature and pressure gradients both increase the moisture availability in the region through a higher moisture flux from the tropical Atlantic and intensifies the monsoon system through strengthened horizontal and vertical winds, resulting in increased rainfall. The study shows that it is challenging to capture correctly multidecadal Sahel precipitation variability in reanalysis data. Reasons for this behavior are discussed.
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1 Introduction

The African Sahel is a water vulnerable region in northern Africa, stretching across the continent from the Atlantic Ocean in the west to the Red Sea in the east. It is a transition region, located between the arid Sahara desert in the north and the humid Central Africa in the south (see Figure 1), with vegetation ranging from semi-desert to wooded grassland (White, 1983). Sahel’s location between the arid Sahara and tropical Central Africa has created a strong climatological precipitation gradient, with annual mean precipitation ranging from approximately 10 mm/month in the northern part to 100 mm/month in the southern edge (see Figure 2).

This limits permanent rain-fed agriculture in the region and for a long time pastoralism has instead been the basis of the economy (White, 1983). Approximately 70-80% of the annual precipitation falls between July and September with the onset of the West African Monsoon (WAM) (see Figure 3) and the vast majority of the biomass is produced during these humid summer months (Herrmann et al., 2005). This climate, and specifically the hydrological cycle, makes the people, agriculture and livestock highly dependent on the arrival and strength of the WAM (Hulme, 2001; Warren, 1995).

During the 20th century the Sahel region experienced extended dry periods and recurring droughts, with severe impacts on the agriculture, livestock and livelihood of the people living in the region (Hulme, 2001). This has emphasized the need for further research in order to understand the inter-annual and inter- to multidecadal rainfall variability in the region.
Figure 2: The annual mean precipitation in mm/month in North Africa from January 1901 to December 2015. Values from the CRU TS 3.24.01 dataset.

Figure 3: The monthly mean precipitation as a percentage of the total annual precipitation in Sahel (10° - 18°N, 20°W - 30°E). Values from the CRU TS 3.24.01 dataset and calculated over the years 1901-2015.
1.1 Dynamics governing the Sahel hydroclimate

1.1.1 Inter-Tropical Convergence Zone and the West African Monsoon

The annual rainfall cycle in the Sahel region is dominated by the arrival of the West African Monsoon (WAM). The WAM is driven by the seasonal movement of the latitudinal band of maximum insolation which shifts northward during the boreal summer. For this reason the onset of the WAM has often been seen as a part of the northward shift of the Inter-Tropical Convergence Zone (ITCZ) and the related Hadley circulation. The rain was thought to be a result of local thermal instability and aided by the convergence of low level northeasterly Harmattan winds from Sahara and southwesterly wind from the Atlantic (Sultan and Janicot, 2003; Nicholson, 2013). This view is true over the oceans, where the low level wind convergence and the maximum rainfall are collocated, but over West Africa they are separated by approximately 1000 km and a revised dynamical system is now used to describe the WAM and its rainfall (Nicholson, 2009; Žagar et al., 2011).

The WAM is initiated by the the development of the Saharan Heat Low, a thermal low located in western Sahara (see Fig. 4), as a result of the northward shift of the latitude of maximum insolation and the low heat capacity of land compared to the ocean. The temperature gradient between the warm Sahara and the cooler Atlantic creates a pressure gradient force at the upper levels directed from land to the ocean, resulting in a divergent wind, a mass transport out from the air column over land and an ensuing low pressure area at the surface. This creates a convergence at the surface with southwesterly low level winds advecting moisture in over West Africa (see Figures 4). The increase of moisture in the boundary layer facilitates the development of convective rain, resulting in the high rainfall related to the West African Monsoon (Goosse, 2015; Holton, 2004).

![Horizontal Wind - 1000 hPa](image)

Figure 4: Horizontal surface winds at 1000 hPa over North Africa during the West African Monsoon. Convergence indicated with black line. Figure based on ERA20C mean July-September values.
1.1 Dynamics governing the Sahel hydroclimate

1.1.2 Easterly Jets and Waves

Connected to the WAM are several tropical dynamical features; the African Easterly Jet (AEJ), Tropical Easterly Jet (TEJ) and African Easterly Waves (AEW) whose roles in determining West African precipitation have been discussed for several years (Cook, 1999; Holton, 2004).

The AEJ is a mid-level wind maxima over Northern Africa, consisting of strong easterly winds (approx. 10-12 m s\(^{-1}\)) located at an altitude of 500-600 mb and with the jet core along the 15\(^{\circ}\)N latitude (see Fig. 5a). The zonal wind is strongest in its western part and decreases towards east. It is a result of the strong positive meridional temperature gradient between the Saharan Heat Low and the Atlantic Ocean, which like the monsoon is created by the difference in summer insolation, the low thermal inertia of the ocean and the negative meridional soil moisture gradient (Cook, 1999). The temperature gradient creates an easterly shear over the surface westerlies, in accordance with the thermal wind relation, resulting in a strong easterly wind. Latent cooling of the surface as a result of the soil moisture strengthens the meridional temperature gradient along the surface, but condensational heating aloft over southern West Africa together with the cooling along the dry adiabat over the Saharan Heat Low results in a reversal of the meridional temperature gradient. The AEJ is located just below this reversal (Cook, 1999).

The TEJ is located in the upper troposphere, at approximately 200 hPa and 7\(^{\circ}\)N and with easterly winds over Africa of around 12 m s\(^{-1}\) (see Fig. 5b). The TEJ is a feature connected to the Indian Monsoon, and similar to the AEJ it is a response to the strong temperature gradient between land and ocean, in this case the Himalayan plateau and the Indian Ocean. Its core is located east of the African continent, over the Indian Ocean, and the intensity decreases towards the west (Nicholson and Grist, 2003; Nicholson, 2009).

Since the mid-1970s African Easterly Waves (AEW) have been linked to the convection and precipitation over West Africa (Nicholson, 2013). They are synoptic-scale wave disturbances with a wavelength of approximately 2500 km, propagating westward at a speed of about 8 m s\(^{-1}\) along two main east-west tracks (Holton, 2004; Nicholson, 2013). The AEJs propagating along the northerly track, located around 18\(^{\circ}\)N – 20\(^{\circ}\)N at an altitude of 850 hPa, are associated with
1.2 Sahelian rainfall variability

The sources of moisture for rainfall in Sahel are many and vary within the region, but they can be divided into two categories: moisture advected from surrounding areas or supplied through local evaporation (Gong and Eltahir, 1996). Many studies agree that the tropical Atlantic and central Africa together with the local recycling of moisture are the main source regions, which suggests that inter-annual variability in transport from these regions has the ability to largely affect the...
1.2 Sahelian rainfall variability

Analysis of rainfall anomalies in the Sahel region has shown variability on several different time scales, from a continuous desiccation to multidecadal regimes of drier (1900s-1920s, 1960s-1980s) and wetter (1920s-1950s) conditions as well as large inter-annual variability (Hulme, 2001; Nicholson et al., 2000). The severe droughts which occurred during the early 1970s emphasized the need for more research into the causes of the dry periods. However, research has at times been hindered by lack of access to rainfall observations from northern Africa, through a lower spacial coverage in general as well as political and economic instabilities making it more difficult for researchers to obtain data from parts of the region (such as Chad, Ghana and the Sudan) (Nicholson et al., 2000).

Many theories have tried to explain the rainfall variability in the Sahel region during the 20th century. Especially important for increased knowledge is separating anthropogenic causes from natural variability and low frequency from high frequency variability.

The desiccation was initially linked to two types of anthropogenic forcing; increasing levels of greenhouse gases in the atmosphere and a degradation of the regional land cover due to changes in the land use, famously known as "Charney’s hypothesis" (Hulme, 2001; Giannini et al., 2003). Charney’s hypothesis (Charney, 1975) describes a potential albedo-precipitation feedback caused by reduced vegetation in Sahel and a subsequent increase of the regional albedo. This causes a sinking motion and suppresses the precipitation, which further degrades the vegetation. Several modeling studies have supported this land use-precipitation theory (Taylor et al., 2002; Sud and Fennessey, 1982), but as they are often forced with exaggerated vegetation conditions many scientists doubt that changes in land use can on its own have created the strong desiccation observed in the second half of the 20th century, although the feedback mechanism might have strengthened it (Hulme, 2001; Giannini et al., 2003; Taylor et al., 2002). Other studies also suggest that the drying trend of the last century was due to anthropogenic forcing, both from increased aerosol loading and increased greenhouse gases in the atmosphere, which together with a large internal variability resulted in the observed precipitation variability (Held et al., 2005).

Studies of the moisture transports to Sahelian-Sudan, located in eastern Sahel, indicate that there is a strong correlation between the total inter-annual rainfall variability in the region and the inter-annual variability of the moisture originating from the Coast of Guinea, central African and western Sahel (Salih et al., 2016). This moisture transport is connected to the WAM which to a large part is driven by the thermally induced pressure gradient between the tropical Atlantic and the Sahara. Studies suggest that the wetter and drier multidecadal regimes are connected to the phases of cold and warm sea surface temperature (SST) anomalies over the North Atlantic (Nicholson et al., 2000; Salih et al., 2016; Zhang and Delworth, 2006).

The alternating cold and warm phases over the Atlantic are referred to as the Atlantic Multidecadal Oscillation (AMO) (Kerr, 2000), and studies indicate that the AMO is a result of internal climate variability linked to the Atlantic Meridional Overturning Circulation (AMOC) (Knight et al., 2005). The AMOC is a part of the Thermohaline Circulation and it transports heat northwards in the surface layers in the Atlantic and cold water southwards in the deep Atlantic. A weaker AMOC would result in less heat being transported in to the upper layers of the North Atlantic, causing anomalously cold SSTs, while a more intense AMOC instead would increase the heat transport to the North Atlantic, resulting in warmer SSTs (Goosse, 2015; Knight et al., 2005). The warm and cold phases of the AMO are believed to impact a variety of regional climate phenomena, for example influencing multidecadal variability in both
Indian and Sahelian rainfall, Atlantic hurricanes and rainfall and river flow in continental US (Knight et al., 2006; Zhang and Delworth, 2006).

Through analyzing high-resolution observational rainfall and SST data from the 20th century, the multidecadal rainfall variability in Sahel as well as the correlation between the AMO and the Sahel rainfall can be investigated. In addition to this, using reanalysis data, which combine observations with a short-term forecasting model, enables us to combine the statistical analysis of the multidecadal rainfall variability in Sahel with a complete dynamical description of the atmosphere. A composite analysis of the atmosphere based on the multidecadal regimes of wet and dry Sahel conditions could give us insight in to the dynamics governing these processes. Increased knowledge of the dynamics influencing multidecadal rainfall variability in Sahel could greatly improve the conditions for long-term seasonal forecasts in the region, aiding in mitigating the severe droughts and other precipitation related extreme weather events. This study therefore aims to investigate three questions:

- How does the precipitation in Sahel vary on a multidecadal scale?
- Is there a relationship between the multidecadal rainfall variability in Sahel and the Atlantic Multidecadal Oscillation?
- Can a dynamic analysis of the atmosphere explain the causes for the multidecadal rainfall variability?

The observational and reanalysis datasets which are used for the analysis are described in section 2, together with the different statistical methods applied. The results are then presented and discussed in section 3 and the conclusions are presented in section 4.

2 Methods and Data

2.1 Data

In this thesis both observational and reanalysis data have been used as a basis for the analysis of the multidecadal precipitation variability in Sahel and the dynamics governing it.

2.1.1 Observations

The precipitation was analyzed using high-resolution gridded observational data from the Climate Research Unit (CRU TS 3.24.01; Harris et al. (2014)) dataset, consisting of monthly mean values for the years 1901-2015. The data is constructed using land-based observations from meteorological stations across the globe, which are interpolated into a grid with 0.5° latitude/longitude resolution to create a globally covering observational dataset. The grid cells cover all land surfaces except Antarctica, but the availability of meteorological stations vary with time and between different regions. Approx. 60-80 % of the grid cells in Africa have station data for most of the 20th century, with lower numbers at the beginning of the century and at the end. Grid cells lacking data are supplied with values equal to the 1961-1990 climatological mean. The CRU TS 3.24 dataset was chosen due to its high spatial resolution and long time series, which increases the statistical reliability when looking at multidecadal variability.

The analysis was initially done using the CRU TS 3.24 dataset but was redone using the 3.24.01 version after the Climate Research Unit published an updated version which addressed, among
other things, corrections in the precipitation field over Sudan for the years 1990-2013.

The rainfall over Sahel, as described by the CRU TS 3.24.01, was also compared to the monthly mean GPCP Precipitation data provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their Web site at http://www.esrl.noaa.gov/psd/ (Adler et al., 2003).

The SST was analyzed using the observational dataset HadISST v1.1 (Rayner et al., 2003) from the UK Met Office Hadley Centre for Climate Prediction and Research, which consists of monthly mean sea surface temperatures spanning the years 1871-2015 and covering all non land-areas at a 1° longitude-latitude resolution. The data is retrieved from in-situ observations and satellite measurements and is interpolated to create a globally complete dataset. The dataset was chosen due to its long time serie and high spatial resolution.

The sea level pressure was analyzed using the HadSLP2 dataset which is a global 5° resolution dataset comprised of land and marine pressure observations for the years 1850-2004 (Allan and Ansell, 2006).

2.1.2 Reanalysis

Reanalysis is a method through which an atmospheric model is used to produce short-term forecasts, which are then corrected using available observations. The data assimilation and the observations are weighed together according to their respective uncertainties. Through this process sparse observations can be used to create a global, dynamically consistent historical dataset, facilitating analysis of atmospheric trends and dynamics.

The atmospheric dynamics were analyzed using the ERA20C Reanalysis dataset (Poli et al., 2016), which is available in daily, invariant and monthly mean values for the years 1900-2010 at a horizontal resolution of approximately 125 km (spectral truncation 159), out of which only the monthly mean values were used. Sea surface temperatures and sea ice concentrations from the HadISST dataset version 2.1.0.0 are used as prescribed forcing for the model, together with data for the solar radiation, tropospheric and stratospheric aerosols, ozone and green house gases as specified for CMIP5 (Taylor et al., 2012). Observational input is comprised of atmospheric pressure and marine wind observations from the International Surface Pressure Databank (ISPD Cram et al. (2015)) version 3.2.6 and the International Comprehensive Ocean-Atmosphere Data Set (ICOADS, Woodruff et al. (2011)) version 2.5.1. The vegetation is invariant. The ERA20C reanalysis dataset was used in order to preserve a dynamical consistency in the analysis when looking at a multitude of variables on a multidecadal scale.

The Sahel rainfall was also compared to precipitation data in the twentieth century National Centers for Environmental Prediction/National Center for Atmospheric Research reanalysis dataset (Compo et al., 2011).

2.2 Methods

In this thesis a multitude of methods are used in order to analyze the multidecadal variability and its period, as well as the dynamical features associated to it. All analysis was performed using the Climate Data Operators (CDO) via the Supercomputer Triolith or using Matlab.
2.2 Methods

2.2.1 Detrending and Low-Pass filter

In order to separate variability in the different datasets occurring on a multidecadal scale two methods were used: detrending and filtering.

**Detrending** is a method through which linear trends in a dataset are identified and removed. This is most often done using the **least squares fit** method where the values in the time series are assumed to be distributed as $N(a+bt,\sigma^2)$ and the linear equation $y = a + bt$ which fit closest to the time series is identified. The constants $a$ and $b$ are chosen so that the sum of the squared residuals (i.e. the distances between the values in the time series and the calculated value by the linear equation) is as small as possible (Wilks, 2011). This trend is then subtracted from the dataset to produce the detrended time series.

Values in datasets can vary on many different time scales, from intra-annual to multidecadal and onward. To filter out variability that is irrelevant to the specific questions being investigated, different filters can be used. There is a multitude of different filters available, and in this thesis a **Butterworth lowpass filter** was used (Emery and Thomson, 2001). The Butterworth filter is a frequency based filter in which you specify which frequencies you would like to let pass through the filter, while the remaining frequencies are attenuated in accordance with the cutoff frequency and order of the filter. The filter is designed so that the magnitude of the signal at the cutoff frequency is decreased to $1/\sqrt{2}$ and the filter order determines how the attenuation occurs. The main purpose is to let the intended frequencies, the passband, completely through the filter while the remaining frequencies are removed. The Butterworth filter can be designed as a lowpass, highpass, bandpass or bandstop filter, and in our case a lowpass filter was used as we wanted to remove the high-frequency variability and only study the low-frequency variability.

The implementation of the Butterworth lowpass filter using Matlab comes in two steps. First the commando `butter` is used, which returns the transfer function coefficients $b$ and $a$. These coefficients are then used in the commando `filtfilt` which performs a zero-phase digital filtering of the input data based on the filter specifications. In this thesis a lowpass Butterworth filter of 4th order and with a cutoff frequency of 10 years is used, meaning it filters out variability with a higher frequency than a 10 year period. The magnitude response of the filter can be seen in Figure 8. A Butterworth filter was in part chosen due to the limiting length of the time series. Only 115 years of precipitation observations are available and if a runmean had been used the time series would have decreased by approx. a decade (depending on the window length), which would have further limited the analysis when looking at multidecadal variability.

2.2.2 Power Spectrum Analysis

To calculate the periods on which different variables such as rainfall and SSTs vary, the power spectrum of a time series is analyzed. One common way of doing this is with a **periodogram method**, one of several nonparametric approaches to identifying the periodicities of time series. As described by Shumway and Stoffer (2011), the periodogram method estimates the power spectrum by performing a fourier analysis on the time series, which is a method of decomposing the time series into its different components, i.e. identifying the different frequencies of a signal. This is done through finding the discrete-time Fourier Transform (DTFT) of the time series which indicate the magnitudes of the different components of the signal. To then compute the power spectrum the result from the DTFT is squared and scaled to the total power in the signal. This gives a measurement of the relative importance of each frequency to the total variability in the data, and is called the **periodogram**. This analysis was performed using the
2.2 Methods

2.2.3 Correlation and Single Value Decomposition (SVD)

Correlation is a measurement of how well two different variables co-vary. In this thesis the Matlab command `corrcoef` was used, which calculates the Pearson correlation coefficient as defined in Equation 1 (von Storch and Zwiers, 1984).

\[
\rho(A, B) = \frac{1}{N-1} \sum_{i=1}^{N} \left( \frac{A_i - \mu_A}{\sigma_A} \right) \left( \frac{B_i - \mu_B}{\sigma_B} \right)
\]

where \(\mu\) and \(\sigma\) is the mean and standard deviation respectively of the variables \(A\) and \(B\) and \(\rho\) is the correlation coefficient.

As a complement to the correlation analysis the Single Value Decomposition (SVD) method was used to investigate the relationship between the North Atlantic SSTs and the North African precipitation. The SVD identifies pairs of spatial patterns, one for each variable, and their temporal variations that are associated with the maximum explained squared covariance between two fields (Bretherton et al., 1992; von Storch and Zwiers, 1984). The pairs are also referred to as modes, as in first mode of variability etc.. The method is described in detail in Bretherton et al. (1992), and the analysis is performed using the guidance of A Manual for EOF and SVD Analyses of Climatic Data (Bjornsson and Venegas, 1997).

The SVD method produces sets of singular vectors, which are spatial patterns, and associated sets of singular values which are a measurement of the covariance explained by each mode. Each pair/mode explains a fraction of the squared covariance between the fields, with the first pair explaining the largest fraction and the succeeding pairs explaining fractions in decreasing order. By projecting the single vectors onto the corresponding original fields for each variable the Expansion coefficients are calculated. The Expansion coefficients are time series, one for each variable, which describe how the modes of variability oscillate in time. The results are visualized using homogeneous correlation, i.e. the correlation between the expansion coefficients and their respective original field.

Figure 8: The magnitude response of a 4th order Butterworth lowpass filter with a 10 year cutoff frequency.


2.2 Methods

2.2.4 Composite Analysis

In order to study the atmospheric conditions during the years of high and low amounts of rainfall in Sahel a composite analysis was performed on several atmospheric variables. This is done through the creation of subsets of the data, whose mean can be compared to the mean state of the atmosphere or to other subsets in order to draw conclusions of the processes and conditions related to the high/low amounts of rainfall (von Storch and Zwiers, 1984). In this study the subsets are based on the lowpass filtered Sahel precipitation index, i.e. the mean July-September (JAS) precipitation, area averaged over Sahel and filtered in order to identify the multidecadal variability. Years with a JAS mean rainfall more than 0.8 standard deviations from the 1900-2010 mean JAS rainfall are identified as belonging to a positive and negative subset and the values are averaged within the subsets.

2.2.5 Significance tests

To examine whether results are statistically significant, significance tests are performed. There exist many different methods for examining the significance, but the purpose of them is always to discern if the null hypothesis can be rejected or not (von Storch and Zwiers, 1984). The null hypothesis depends on the analysis being performed: when examining the significance of the correlation between two variables the null hypothesis is that there is no relationship between the two variables but when examining the significance of a composite the null hypothesis is that the means of the subsets belong to the same normal distribution.

The significance of the correlation is calculated using the Student’s t-distribution, which is a distribution specific for each degree of freedom, by first calculating the t-value (see Eq. 2).

\[ t = r \sqrt{\frac{n-2}{1-r^2}} \]  

where \( t \) is the t-value, \( r \) is the correlation coefficient and \( n-2 \) is the degrees of freedom, where \( n \) is the sample size. The t-value is compared to the Student’s t-distribution using a cumulative distribution function with the Matlab commando \texttt{tcdf} (Student’s t cumulative distribution function). The \texttt{tcdf} gives a value for the probability of a t-value less or equal to \( t \) if the null hypothesis is not rejected, meaning that if the \texttt{tcdf}-value is equal to or larger than 0.95 the correlation is considered significant at the 95% level.

The t-test described above is the most valid under the assumption of independence, but meteorological parameters are often auto-correlated which affects the degree of freedom and through that the t-value (von Storch and Zwiers, 1984). To take the auto-correlation into account the effective degree of freedom \( N^* \) is calculated and replaces the degree of freedom in Equation 2 as well as when using the Matlab commando \texttt{tcdf}. This is done using the Modified Chelton method as described by Pyper and Peterman (1998), using Equation 3.

\[ \frac{1}{N^*} \approx \frac{1}{N} + \frac{2}{N} \sum_{j=1}^{\infty} \rho_{XX}(j)\rho_{YY}(j) \]  

where \( N \) is the sample size and \( \rho_{XX}(j) \) and \( \rho_{YY}(j) \) are the auto-correlations of the two time series at a lag \( j \).

The significance of the composite analysis is examined using the two-sample t-test (see Equation 4), as described by Wilks (2011), and performed using the Matlab commando \texttt{ttest2}. The null
hypothesis is that the data, in this case two subsets, come from two independent samples from normal distributions with equal means, and if it is rejected it would indicate that the data come from two samples of unequal means.

\[ t = \frac{\bar{x} - \bar{y}}{\sqrt{\frac{s_x^2}{n_x} + \frac{s_y^2}{n_y}}} \]  

(4)

where \( \bar{x} \) and \( \bar{y} \) are the sample means, \( s_x \) and \( s_y \) are the standard deviations of the samples and \( n_x \) and \( n_y \) are the sample sizes.

The significance of the peak periods calculated using the Power Spectrum Analysis were analyzed using the method described for Spectral Analysis in the book *Statistical Methods in the Atmospheric Sciences* (Wilks (2011); Equation 8.81). The null-hypothesis is that the peaks in the power spectrum are significantly larger than the red-noise spectrum at that frequency.

### 2.3 Definition of the Sahel precipitation and AMO indices

To examine the multidecadal precipitation variability in Sahel a Sahel Precipitation Index (SPI) is created. This is done by averaging the precipitation over a defined area, using area weighting to take into account the difference in grid size within the area. In this thesis Sahel is defined as the area 10° – 18° N and 20° W - 30° E. Further east in Sahel, rainfall is found to be partially influenced by other dynamical features compared to western Sahel which is why the easternmost region was excluded when creating the Sahel index. Eastern Sahel is for example influenced more by the Indian Ocean, the El Niño-Southern Oscillation (ENSO) and Mediterranean synoptic systems, and associated to the Indian Monsoon rainfall (Nicholson et al., 2000; Bhatt, 1989). The Sahel region is indicated in Figure 9.

![Figure 9: The areas used for the Sahel precipitation index (black) and the AMO index (blue).](image)

The AMO index is created by calculating an area average of the North Atlantic SSTs, i.e. ocean areas 0 – 60° N and 75° - 7.5° W (indicated in Figure 9). As with the Sahel index, an area weighting is used to take into account the difference in grid size at the different latitudes and grid points covered by ice are excluded. Both the SPI and the AMO index refers to the detrended and low-pass filtered time series.
3 Results and Discussion

3.1 Multidecadal Variability

3.1.1 Rainfall variability in Sahel

The summer monsoon rainfall in Sahel (averaged over the Sahel region as described in Section 2.3 and over the months July, August and September) is presented in Figure 10 for the CRU observational data (year 1901-2015). The same analysis of the July-September Sahel rainfall is performed for the ERA20C reanalysis, year 1900-2010 (not shown). The trend is calculated and presented in the figure as a trend line. The mean Sahel JAS rainfall in CRU is 136 mm/month, which is approximately 50% larger than the mean JAS rainfall of 89 mm/month in the ERA20C reanalysis dataset. Both the CRU and ERA20C datasets show an insignificant trend for the Sahel JAS rainfall of -1.2 mm/decade and 1.1 mm/decade respectively. The standard deviation of the ERA20C rainfall is at 25 mm/month approx. 40% larger than the CRU at 18 mm/month standard deviation. The CRU JAS rainfall in Sahel is also compared to the GPCP dataset which is available for the years 1979-2015 (2016 excluded as not full monsoon season is available) and calculated using the same method as for the CRU JAS Sahel rainfall. The correlation between the GPCP and CRU JAS Sahel precipitation is $R = 0.95$, significant at 99%, which emphasizes that the observations exhibit low uncertainty.

![Sahel Precipitation - Observational data: 1901-2015](image.png)

**Figure 10**: The raw JAS rainfall in Sahel based on the CRU observational dataset for the years 1901-2015, in mm/month (blue) and the GPCP dataset for the years 1979-2015 (yellow). The trend during the period is -1.2 mm/decade (red).
3.1 Multidecadal Variability

To isolate the multidecadal variability the raw time series are detrended and a Butterworth lowpass filter is applied, creating the Sahel Precipitation index (SPI). A power spectrum analysis is also performed in order to estimate the periods of the rainfall variability. The CRU data shows a clear multidecadal rainfall variability, with regimes of dryer conditions in decades 1900-1920 and 1970-2000 and wetter conditions 1920-1970 and 2000 onward (Figure 11a). Clear multidecadal rainfall variability is also visible in the ERA20C dataset, with dry conditions during the decades 1940-1970 and wetter conditions 1920-1940 and 1970-2000 (Figure 11b). The power spectrum analysis of the Sahel rainfall displays a clear, significant maximum for periods between 60 and 80 years for both the CRU observational and ERA20C reanalysis data (Figures 12a and 12b). The correlation between the lowpass filtered CRU and ERA20C Sahel JAS rainfall is $R = -0.34$ (see Table 1), which corroborates that the two datasets are uncorrelated and exhibits opposite rainfall regimes throughout most of the 20th century.

![CRU Sahel precipitation - Low-pass filtered and Raw data](image1)

![ERA20C Sahel precipitation - Low-pass filtered and Raw data](image2)

Figure 11: The detrended and lowpass filtered Sahel JAS rainfall for (a) CRU (1901-2015) and (b) ERA20C (1900-2010) together with the detrended raw time series (black). Values are normalized using the standard deviation of the respective time series.

![CRU observational data - Power Spectrum](image3)

![ERA20C reanalysis data - Power Spectrum](image4)

Figure 12: The power spectrum of the detrended timeseries of the JAS rainfall in Sahel from (a) CRU and (b) ERA20C. Peaks indicate periods dominating the variability and are shown in red, and the 95% confidence limit based on a red-noise null hypothesis is shown in orange.
3.1 Multidecadal Variability

The application of a Butterworth highpass filter on the detrended time series using the same cutoff frequency (10 years) shows a correlation of $R = 0.55$, statistically significant at 99%, between the CRU observational and ERA20C reanalysis JAS rainfall over Sahel, which indicates that although the ERA20C reanalysis reproduces a multidecadal variability out of phase with the observations, it does capture the high frequency variability (see Figure 13). We can also see that the ERA20C captures the seasonal cycle of the rainfall in Sahel, indicating that the West African Monsoon is well described in the forecast model used in the reanalysis (Figure 14). We therefore decide that the time series based on the ERA20C Sahel rainfall will be used when performing the composite analysis on the different ERA20C variables, in order to examine the dynamical processes governing the multidecadal variability within the ERA20C reanalysis dataset.

Figure 13: The highpass filtered CRU observational (black) and ERA20C (green) reanalysis time series of the Sahel JAS rainfall, using a 4th order Butterworth highpass filter with a 10 year cutoff frequency. The time series have a correlation of $R = 0.55$, significant at 99% and calculated over the years 1901-2010.

Figure 14: The seasonal cycle of the Sahel rainfall, presented as a monthly percentage of the total annual rainfall, as described by the CRU observational and ERA20C reanalysis datasets. The monthly values represent the monthly mean over their respective time series: 1901-2015 (CRU) and 1900-2010 (ERA20C).

3.1.2 SST variability in the North Atlantic

The North Atlantic SSTs are averaged over each year, creating an annual mean value averaged over the latitudes and longitudes specified in Section 2.3 for the years 1901-2015. Detrending and applying a Butterworth lowpass filter to the timeseries emphasizes the multidecadal variability in the North Atlantic SSTs (Figure 15a) for the HadISST observational dataset. The North Atlantic experienced warm anomalies in the decades 1920s-1950s and 1990s onward and cold anomalies 1910s-1920s and 1950s-1990s. The power spectrum analysis of the time series shows a maximum for periods between 50 and 70 years (Figure 16a), close to that of both the CRU and ERA20C rainfall variability. The multidecadal variability of the North Atlantic SSTs in the ERA20C reanalysis dataset shows similar warm/cold regimes, with lower temperatures in the 1900s-1920s and 1960s-1990s and higher temperatures in the 1920s-1960s and 1990 onward (Figure 15b). This area averaged, detrended and lowpass-filtered annual mean North Atlantic SSTs is referred to as the AMO index. The correlation between the HadISST AMO index and the ERA20C AMO index is $R = 0.73$ (significant at 99%), and the power spectrum analysis shows that periods between 60 and 80 years dominates the SST variability (Figure 16b).
significance of these maxima could not be demonstrated due to the limited length of the HadISST and ERA20C time series.

![AMO index: HadISST](image)

(a) HadISST AMO index

![AMO index: ERA20C sst](image)

(b) ERA20C AMO index

Figure 15: The detrended and lowpass filtered AMO index for (a) HadISST (1901-2015) and (b) ERA20C (1900-2010) together with the detrended raw time series (black). Values are normalized using the standard deviation of the respective time series.

![HadISST observational data - Power Spectrum](image)

(a) HadISST

![ERA20C reanalysis data - Power Spectrum](image)

(b) ERA20C

Figure 16: The power spectrum of the detrended timeseries of the North Atlantic SSTs for (a) HadISST and (b) ERA20C. Peaks indicate periods dominating the variability and are shown in orange.

When comparing the CRU SPI and HadISST AMO index, one can see that the wet/dry and warm/cold periods largely coincides. However, the correlation between the two timeseries is $R = 0.25$ and is not significant (Table 1). The correlation between the HadISST AMO index and the ERA20C SPI is $R = -0.04$, and between the ERA20C AMO index and SPI the correlation is $R = -0.08$, i.e. no correlation. The correlation between the CRU SPI and the ERA20C AMO index is $R = 0.61$, i.e. higher than the correlation between the CRU SPI and the observational HadISST AMO index. The correlations between the raw time series are lower than for the low-pass filtered time series for all variables except for the correlation between the two AMO
indexes. The correlation between the raw HadISST and ERA20C AMO indexes is $R = 0.79$, significant at 99%.

<table>
<thead>
<tr>
<th></th>
<th>CRU pre</th>
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<th>ERA sst</th>
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<td>ERA pre</td>
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<td>HadISST</td>
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<td>ERA sst</td>
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Table 1: Correlation between low-pass filtered CRU Spi, HadISST AMO index and ERA20C Spi and AMO index. Correlation of raw (unfiltered) time series within brackets. Results significant at 95% is shown in bold.

### 3.2 Correlation of multidecadal variability

#### 3.2.1 Global field correlation: Sahel rainfall and global SSTs

As the analysis showed a very week correlation between the AMO index and the CRU Spi, a global field correlation between the detrended and low-pass filtered global SST anomalies and the CRU Spi was instead performed in order to ascertain if a more limited area in the North Atlantic has a higher correlation to the Sahel JAS rainfall on a multidecadal scale. Figure 17 showed that the highest correlation was located along a latitudinal band in the mid latitudes as well as in the sub polar region, with values around $R = 0.8$. The correlation is significant at 95%, with auto-correlation taken into account. The correlation also shows a clear dipolar character, with mainly positive correlations on the northern hemisphere and negative correlations in the southern hemisphere.

![Correlation between Sahel rainfall and global SSTAs](image_url)

Figure 17: The correlation between the Sahel precipitation (CRU Spi) and the global SST anomalies (HadISST) for the years 1901 - 2015. The 95% significance is marked with black contours.
3.2 Correlation of multidecadal variability

The global field correlation between the ERA20C SSTs and precipitation showed no significant correlation in the Atlantic (figure not shown), consistent with the ERA20C SPi being out of phase with the observational and reanalysis signal of the AMO.

3.2.2 Co-varying mode of Sahel rainfall and North Atlantic SSTs

To further analyze the statistical relationship between the Sahel precipitation (CRU) and North Atlantic SSTs (HadISST) a SVD analysis is used. Applying the method on detrended annual mean SSTs in the Northern Atlantic (0° – 70° N and 80° W - 30° E) and JAS precipitation in Africa north of the Equator (0° – 35° N and 20° W - 30° E) results in a first mode which explains 68% of the total variability. Please note that the processing of the raw data has removed variability connected to the seasonal cycle. The lowpass filtered expansion coefficients for the first mode (SVD1) for the SSTs and precipitation have a correlation of \( R = 0.84 \) which is significant at 99%. The time series show similar positive/negative regimes as the CRU Sahel precipitation and HadISST AMO index (Figure 18). The expansion coefficients are lowpass filtered using a 13 year runmean.

![Expansion coefficients for SVD1](image)

Figure 18: The expansion coefficients for the first SVD mode (SVD1) of the CRU precipitation and HadISST SSTs, low-pass filtered using a 13 year runmean. The correlation is \( R = 0.84 \), significant at 99% when taking autocorrelation into account.

To visualize the regions connected to the first SVD mode, a homogeneous field correlation is performed between the SST and precipitation expansion coefficients and their respective detrended raw HadISST and CRU datasets. The results show a clear correlation between the first SVD mode and the SSTs in the subpolar and eastern North Atlantic (Figure 19a), similar to the pattern seen in the correlation between the detrended and lowpass filtered Sahel
precipitation and the Atlantic SSTs (Figure 17). Figure 19b shows a strong homogeneous correlation between expansion coefficient for the precipitation and the precipitation in Sahel, centered along 15°N.

Figure 19: Homogeneous correlation between (a) the SST expansion coefficient of first SVD mode and the detrended SSTs in the North Atlantic (HadISST) and (b) the precipitation expansion coefficient of first SVD mode and the detrended JAS precipitation in the North Africa (CRU).

3.3 Mechanisms of the multidecadal variability

The composites in this thesis are based on two different sets of subsets, one is based on the SPI as described by the CRU observational precipitation data and one on the SPI as described by the ERA20C reanalysis data. The years used for the positive and negative subsets for each composite can be seen in Figures 20a and 20b, and the composites are presented as the difference between the positive and negative subsets.

Figure 20: Lowpass filtered JAS rainfall over Sahel. Years used for positive(red) and negative(blue) subsets in the composite analysis based on (a) the CRU SPI and (b) the ERA SPI are indicated.
3.3 Mechanisms of the multidecadal variability

3.3.1 Spatial pattern of multidecadal variability: Rainfall and SSTs

A composite based on the CRU SPI is first used to examine the observational precipitation and SST pattern connected to the multidecadal precipitation variability, using positive and negative subsets defined as years with 0.8 standard deviations from the mean JAS precipitation. Figure 21a shows the difference between positive and negative years and one can see that the precipitation increases (decreases) in Sahel with maximum values located just south of 15°N, while it decreases (increases) along the Coast of Guinea and in Central Africa in wet (dry) years. The composite is significant at 95% in the entire Sahel. The SSTs show positive (negative) anomalies in the North Atlantic, with the highest values in latitudinal bands along 15°N and 30 – 45°N as well as in the subpolar North Atlantic in wet (dry) years (Figure 21b). The composite also indicate negative (positive) anomalies in the South Atlantic, with significant values only south of 15°S in wet (dry) years (not shown). This pattern is similar to the one produced with both the field correlation and SVD homogeneous correlation, seen in Figures 17 and 19a.

![Composite difference of (a) the CRU July-September mean precipitation in mm/month and (b) the HadISST annual mean SSTs in K, based on the CRU SPI. Composite difference of (c) ERA20C July-September mean precipitation in mm/month and (d) ERA20C annual mean SSTs in K, based on the ERA SPI. Only result significant at 95% is shown.](image)

Figure 21: Composite difference of (a) the CRU July-September mean precipitation in mm/month and (b) the HadISST annual mean SSTs in K, based on the CRU SPI. Composite difference of (c) ERA20C July-September mean precipitation in mm/month and (d) ERA20C annual mean SSTs in K, based on the ERA SPI. Only result significant at 95% is shown.

Figure 21c shows the composite difference for the ERA20C JAS precipitation, based on the ERA SPI. We can see that the precipitation in Sahel increases in wet year and decreases is dry...
years along a latitudinal band approximately $7^\circ$ – $14^\circ$N, with the highest anomalies located in central Sahel and at the Ethiopian Highlands, but the signal also extends to cover the majority of North Africa. The composite is significant at 95% across the entire Sahel. Figure 21d shows the composite difference for the ERA20C SSTs in the North Atlantic based on the ERA SPi, which exhibits colder temperatures in the Tropical North Atlantic and the Subpolar region together with a warm temperature anomaly in the mid-tropics. This is, with an exception of the mid-tropics, opposite to the signal observed in the HadISST composite (Figure 21b), and the result is also only significant in a more limited region.

### 3.3.2 Modulating monsoon strength: Pressure and temperature

The composite difference between the wet and dry subsets for the CRU JAS surface temperature, using the CRU SPI, indicates a cooling of the Sahel region and a warming of the Sahara (see Figure 22a). Figure 22b shows the composite difference based on the CRU SPI for the HadSLP JAS sea level pressure, which exhibits a deepening of the low surface pressure in Sahara and an elevated surface pressure in Sahel in wet compared to dry years. This indicates a strengthening(weakening) of the meridional surface pressure gradient in Northern Africa in wet(dry) decades.

![Composite difference of the July-September (a) CRU mean surface temperature in K and (b) HadSLP sea level pressure in hPa, based on the CRU SPI. Composite difference of the ERA20C July-September (c) mean 2 meter temperature in K and (d) mean sea level pressure in hPa, based on the ERA SPI. Only result significant at 95% is shown.](image)
Figure 22c shows the composite difference of the ERA20C JAS 2 meter temperature anomalies over northern Africa based on the ERA SPI. One can see that there is a significant warming across Sahara in wet compared to dry years, and the signal is present 15 – 30° N across the entire width of North Africa. South of this there is instead a cooling, reaching from the Coast of Guinea to approximately 15°N. Collocated with the temperature anomalies are July-September anomalies in the ERA20C sea level pressure--; negative anomalies across Sahara and northern Sahel with maximum values over eastern Sahara and positive anomalies over central Africa reaching up to 15°N (Figure 22d). These results do together indicate a strengthening(weakening) of the Saharan Heat Low and a northward shift of its eastern part in wet(dry) years, possibly caused by a surface warming(cooling).

### 3.3.3 Atmospheric state related to multidecadal rainfall variability in Sahel

For the remainder of the composite analysis the ERA20C SPI will be used to create positive and negative subsets of variables from the ERA20C in order to examine the processes driving the multidecadal rainfall variability in Sahel within the reanalysis dataset. The composites are produced as the difference between the positive and the negative subsets and only results significant at 95% are shown.

Looking at the total column water vapour (Figure 23) one can see that there is an increase in water vapour over almost the entire African continent north of the Equator in the positive years compared to the negative. The maximum values are centered around a latitudinal band 15°N, which is slightly north of the area of maximum increase of precipitation seen in Figure 21c. In Figure 24, which shows the vertical integral of the water vapour flux, one can see that there is also a strong increase of water vapour fluxes from the Tropical Atlantic, across the Coast of Guinea bringing moisture into southern Sahel, indicating a strengthening of the westerly monsoon flow. There is also an increase in easterly water vapour fluxes over central North Africa, located 15 – 20°N, as well as southerly anomalies located over eastern Sahel and Sahara which indicate an increase in water vapour being transported with the AEJ and a northward shift of the low level convergence in eastern Sahel respectively.

![Figure 23](image1.png)

**Figure 23**: Composite of the ERA20C total column water vapour in $kgm^{-2}$, based on the ERA20C SPI. The results significant at 95% is shown.

![Figure 24](image2.png)

**Figure 24**: Composite of the ERA20C vertically integrated water vapour flux in $kgm^{-1}s^{-1}$, based on the ERA20C SPI. Significant region shown in Figures S1.5a and b.
As the variables represent vertical integrals or accumulations of the total column it is difficult to ascertain the exact level and thus process which contributes to the signal seen in the figures. We will therefore also look at both the specific humidity and the horizontal and vertical winds at different pressure levels in order to distinguish between different dynamical features.

The composite difference of the specific humidity at the 600 hPa pressure level shows a maximum increase located at 15 − 20°N over central Sahel with a dual tail over western Africa (Figure 25). This increase is consistent both with the region of ascent as well as the location of the African Easterly Jet over Sahel and its dual tail over West Africa.

Looking at the composite of the horizontal wind at 1000 hPa in Figure 26a, one can see that the area of low level convergence over central and eastern Sahel has shifted northward as a result of the shift of the low pressure area, resulting in southerly anomalies along 15°N. There is a slight strengthening of the westerly monsoonal flow from the Tropical Atlantic in over the Coast of Guinea and the continent as well as the northeasterly flow from the Mediterranean to western Sahara. The composite of the 850 hPa horizontal wind shows a very similar but more pronounced pattern over Sahel and Sahara, with a northward shift of the winds connected to the low level convergence over eastern Sahara and Sahel (Figure 26b). The westerly anomalies over the Tropical Atlantic and the Coast of Guinea indicates a strengthening of the monsoon flow during the years of high precipitation. There are also northerly anomalies along the African westerly coast, possibly bringing more moisture to the monsoon flow from the warmer eastern North Atlantic in years of high precipitation.
3.3 Mechanisms of the multidecadal variability

RESULTS AND DISCUSSION

Figure 26: Composite difference of the ERA20C horizontal wind at the (a) 1000 hPa pressure level and (b) 850 hPa pressure level in $m s^{-1}$, based on the ERA SPi. Arrows indicate the direction of the anomalies and the significance of the $u$ and $v$ composites can be seen in Supplement I, Figures S1.1a, S1.1b, S1.2a and S1.2b.

The composite of the 550 hPa horizontal wind, seen if Figure 27a, shows strong easterly anomalies along a latitudinal band 15$^\circ$N across the entire continent, indicating a strengthening of the easterly winds connected to the African Easterly Jet and a northward shift of its eastern flank. The southerly anomalies between northeastern Sahara and the Mediterranean is consistent with the northerly shift of the mid level divergence connected to the eastern part of the Saharan heat low. Over the Coast of Guinea strong westerly anomalies indicate a weakening of this regions predominantly easterly flow connected to the AEJ, and possibly a vertical extension of the low level westerlies. The 200 hPa horizontal wind composite shows clear easterly anomalies over the Tropical Atlantic, consistent with the TEJ having widened in the southerly direction as well as slightly strengthened over central Africa (Figure 27b). The meridional anomalies, which are northerly, could also indicate an increased divergence connected to the TEJ and the upper level of the ascent region.

Figure 27: Composite difference of the ERA20C horizontal wind at the (a) 550 hPa pressure level and (b) 200 hPa pressure level in $m s^{-1}$, based on the ERA SPi. Arrows indicate the direction of the anomalies and the significance of the $u$ and $v$ composites can be seen in Supplement I, Figures S1.3a, S1.3b, S1.4a and S1.4b.
3.3 Mechanisms of the multidecadal variability

Looking at the 850 hPa vertical wind composite difference (Figure 28b) one can see that the two ascent regions located at 5°N and 20°N over western Africa, connected to the frictional uplift and Saharan Heat Low respectively (seen in Figure 28a), are strengthened in years with high precipitation compared to those with low precipitation. They are also more clearly separated with a strengthened descent region between them. The eastern part of the ascent region, which is low pressure induced and in the climatological mean lies between 10 and 20°N and merges with the other the branches at approximately 10°N, is strengthened in its northern edge and weakened in its southern, consistent with the low pressure area having shifted northward. At 650 hPa, where the climatological mean shows a single ascent region located over all of the Coast of Guinea, Central Africa and Sahel, from the Equator to 15°N (see Figure 29a), the composite shows a general strengthening of the ascending air over West Africa and a northward shift over the eastern parts of the continent (Figure 29b).

Figure 28: ERA20C vertical velocity JAS (a) mean and (b) composite difference, based on the ERA SPi, at the 850 hPa pressure level in Pa s\(^{-1}\). Only composite results at 95% significance is shown.

Figure 29: ERA20C vertical velocity JAS (a) mean and (b) composite difference, based on the ERA SPi, at the 650 hPa pressure level in Pa s\(^{-1}\). Only composite results at 95% significance is shown.
3.4 Discussion

3.4.1 Datasets

The results show that the ERA20C reanalysis dataset does not capture the timing of the multidecadal wet and dry regimes which have affected the Sahel region during the 20th century, nor does it capture the mean amount of rainfall which falls during the monsoon season. In spite of this the ERA20C captures both the seasonal cycle and the inter-annual variability well, indicating that the monsoon is reasonably well described in the forecast model used in the reanalysis (see Figures 13 and 14). The fact that the Sahel rainfall exhibits a clear multidecadal variability with the same dominating period in ERA20C as in the CRU rainfall still makes it suitable for multidecadal analysis compared to other reanalysis datasets with the same length. The NOAA 20C reanalysis dataset does for example exhibit a dominating period of 19.7 years in the detrended and low-pass filtered Sahel rainfall and no such clear and pronounced multidecadal wet/dry regimes as are visible in the CRU dataset (see Figure 30).

![Figure 30: Detrended and lowpass filtered Sahel precipitation as described by the NOAA 20C reanalysis dataset.](image)

The scarcity of precipitation observations in Africa, as described in Section 2, could affect both the reliability of the CRU observations as well as the analysis in it self. When observations are missing from a grid point the climatological mean in instead inserted, which could account for the relatively small anomalies in the first decades in the dataset when the observational coverage is at its lowest. As the composite is based on years deviating ±0.8 standard deviation from the mean in the detrended and low-pass filtered Sahel Precipitation time series this should not have a large affect on the composites. The strong correlation between the CRU and the GPCP datasets also strengthens the reliability of the last decades values in the CRU dataset, even though the level of observational coverage decreased in this period.
One difficulty when analyzing multidecadal periodicity is the availability of long time series, or specifically lack thereof. Delworth and Mann (2000) state that the length of the currently available instrumental (non-proxy) records, i.e. 100-150 years, is not enough for definitive multidecadal analysis, even though it can produce interesting insights. In this case the Sahel rainfall and the North Atlantic SSTs exhibit periods of 60-80 and 50-70 years respectively, meaning that the time series contain almost 2 cycles. However, in spite of this limitation when calculating the exact length of the dominating multidecadal period, the dynamics governing the different regimes can still be analyzed using datasets containing centennial length time-series.

As the ERA20C SST dataset exhibits the dipolar AMO pattern with a warming/cooling of the northern/southern hemisphere in positive years and the opposite in negative years (figure not shown), the reason behind the out-of-phase multidecadal rainfall variability in Sahel could lie in the atmosphere-ocean interaction. The land surface temperature over northern Africa in the ERA20C dataset replicates the dipolar pattern of the AMO (positive temperature anomalies in the north and negative in the south) but it occurs when the AMO is in the opposite phase. A possible reason for this could be a delay in the temperature advection from the warm North Atlantic, which as it strengthens/weakens the thermal pressure gradient causes the phase shift. However, dynamically it seems that it is the sea level pressure which drives the multidecadal rainfall variability in Sahel and it is also possible that the assimilation of the pressure signal results in the temperature signal over northern Africa.

Figures 22b and 22d show that the composite difference of the sea level pressure is consistent with the stronger/weaker WAM; the stronger pressure gradient coincides with the increase of rainfall in Sahel on a multidecadal scale for both the observational datasets (CRU and HadSLP) and reanalysis datasets (ERA20C). This can also be seen by comparing the strength of the meridional pressure gradients and the rainfall in Sahel. Figures 31a and 31b shows the JAS Sahel rainfall together with the sea level pressure gradient, calculated as the difference between two latitudinal bands (5°W-25°E) at 20°N and 7°N. The gradient is normalized and multiplied by -1 so that a positive value is equal to a stronger (negative) meridional pressure gradient between the Coast of Guinea and Sahara. We can see that the meridional pressure gradients are well correlated with the Sahel rainfall for both the reanalysis and the observational datasets, with a correlation of $R = 0.60$ and $R = 0.18$ for the raw time series and $R = 0.80$ and $R = 0.50$ for the low-pass filtered time series respectively. The correlations for the low-pass filtered time series are significant at 95%.

The sea level pressure gradients over Sahel in the observational and reanalysis datasets are uncorrelated both for the raw and low-pass filtered time series. Further analysis of the consistency between the ERA20C and the International Surface Pressure Databank (the dataset used for assimilation) sea level pressure in Africa north of the Equator on a multidecadal scale is suggested.

The lack of agreement between the ERA20C reanalysis data and observational data on a multidecadal scale over Sahel needs to be further analyzed and hopefully resolved in future reanalysis products. The implementation of a fully coupled ocean-atmosphere model might improve the reanalysis in regions such as Sahel, where the climate is highly dependent on land-ocean interactions and contrasts. Using a coupled ocean-atmosphere model allows for realistic and dynamically consistent surface fluxes and feedback between the upper ocean and lower atmosphere, which should improve descriptions of SSTs, wind, rainfall and surface fluxes linked to these processes (Laloyaux et al., 2016).
3.4 Discussion

3. RESULTS AND DISCUSSION

(a) Observational dataset: CRU and HadSLP

(b) Reanalysis dataset: ERA20C

Figure 31: July-September Sahel rainfall (blue) and meridional pressure gradient (red) for (a) the observational CRU and HadSLP datasets and (b) the ERA20C reanalysis dataset.

A preliminary analysis of mean sea-level pressure and total precipitation was conducted also for the coupled reanalysis CERA20C. Results are shown in Figures 32a and 32b and we can see that the CERA20C has a representation of the Sahel July-September rainfall which to some extent agrees better with the CRU observations (for example mid 70s-80s) but it’s not a vast improvement. The relationship between the Sahel rainfall and the SLP gradient is still significant, with a correlation of $R = 0.78$ on a multidecadal, low-pass filtered scale and $R = 0.60$ for the raw, detrended time series.

3.4.2 Multidecadal rainfall dynamics

The results clearly shows that the Sahel rainfall, as described in CRU, has a pronounced multidecadal variability with a period of 60-80 years and a high, statistically significant correlation to the North Atlantic SSTs. The correlation is even higher between the CRU SPI and the ERA20C
3.4 Discussion

3 RESULTS AND DISCUSSION

AMO index. The SSTs in the ERA20C are identical to the HadISST dataset v.2 (which is used as forcing in the reanalysis), and a reason for the higher correlation could be improvements done to the observational HadISST v.2 dataset. These results are consistent with previous studies and further emphasize the statistical link between the multidecadal Sahel rainfall and the North Atlantic SSTs, specifically the AMO (Zhang and Delworth, 2006).

The results also indicate that the multidecadal variability is driven by a strengthening/weakening of the thermally induced pressure gradients between Sahara and the Coast of Guinea for both the observational and reanalysis datasets. The cooling seen over Sahel and central Africa in July-September is likely caused by the increased rainfall, which lowers surface temperatures through evaporative cooling, but the higher temperatures across Sahara could be a result of temperature advection from the elevated temperatures of the North Atlantic and Mediterranean connected to the AMO. The temperature increase over Sahara would then deepen the Saharan Heat Low, strengthening the meridional pressure gradient driving the WAM.

The ERA20C composite of sea level pressure and 2 meter temperature in March-May exhibits the same pattern of a strengthened meridional pressure and temperature gradient (not shown). The cooling over Sahel and the Coast of Guinea is less pronounced, further indicating that it is a result of the increased monsoon rainfall. The slight cooling could be a result of memory within the reanalysis model from increased rainfall in the previous monsoon season or caused by lower temperatures in the adjacent South Atlantic. In contrast, the higher temperatures and accompanying lower sea level pressure over Sahara is present already in this season. This further indicates that the strengthened temperature and pressure gradient is the cause for the strengthened WAM and increased precipitation.

The strengthened sea level pressure gradients in JAS cause an increased moisture transport across the Coast of Guinea from the Tropical Atlantic to the Sahel, supplying the north African continent and WAM with more moisture (seen in Figure 24). The strengthened meridional temperature gradient strengthens the AEJ which together with the northerly anomalies connected to the TEJ strengthens the uplift located over the rain belt.

While the composite difference for the observational dataset (HadSLP) exhibits a general strengthening of the meridional sea level pressure gradient across the Sahel in JAS, the ERA20C composite has its strongest signal in East Sahel where it not only indicates a strengthened gradient but also a northward shift of the same, resulting in the east-west difference seen in the composites. This produces a northward shift of the low-level convergence over eastern Sahel, seen in the southerly anomalies in the low-level horizontal wind over central and eastern Sahel (Figures 26a and b). The eastern part of the AEJ is shifted northward as a result of the shift of the temperature gradient, as is the ascent region which is located between the AEJ and TEJ axes.

Earlier studies have focused on comparing atmospheric and surface conditions for specific years of high and low rainfall, without separating high-frequency influence and variability from low-frequency (Nicholson, 2009; Grist and Nicholson, 2001). By basing the composite analysis on low-pass filtered data the results in this thesis strengthens the conclusion that a strengthening/weakening of the thermally induced meridional sea level pressure gradients appears to be the driving mechanism behind the wet and dry Sahel conditions also on the multidecadal scale.

Nicholson (2009) suggested that during years of high precipitation the ascension connected to the ITCZ and Saharan Heat Low over West Africa merges with the core of ascent connected to the rainfall, removing the descending branch which separates them and causing precipitation to
reach further north. This is not supported by our composite analysis of the ERA20C reanalysis dataset, instead the descent region is strengthened and the two ascent regions are more clearly separated. However, when comparing the CRU and the ERA20C rainfall composites over North Africa one can see that they exhibit some spatial differences. The observations show an increase of precipitation over Sahel and a slight decrease along the Coast of Guinea and over Central Africa in wet years compared to dry, indicating a northward shift of the rainfall as well as an increase. The ERA20C composite shows a general increase/decrease from the Coast of Guinea and Central Africa up to north of Sahel and a northward shift in eastern Sahel, but no decrease along the Coast of Guinea or over Central Africa. This indicates that the ERA20C mainly describes an increase in precipitation over West Africa, not a shift as is visible in the observations. A possible mechanism behind this discrepancy could be the lack of an interactive vegetation in the ERA20C reanalysis model. The increase in rainfall in Sahel would create a greening, lowering the albedo and causing a warming in the region which affects the meridional pressure gradients. A greening could then result in a northward shift of the West African Monsoon, weakening the descending branch as suggested by Nicholson (2009). A lack of an interactive vegetation could thus explain both the spatial difference in rainfall over West Africa and the persistent separation of the ascending branches. More research on reanalysis and model data produced using an interactive vegetation could give further insight into this aspect of the WAM.

Several studies have emphasized the important role of the African Easterly Waves in the dynamics governing rainfall over Sahel (Nicholson, 2009; Gu et al., 2004), but their short time scale of approximately 3-5 and 6-9 days makes it difficult to analyze their role in multidecadal variability using low-pass filtered datasets in which all variability acting on a period shorter than 10 years is attenuated. Many studies have compared both differences in how frequent they are and differences in their behavior between years of high and low rainfall (Grist, 2002; Grist and Nicholson, 2001), but without filtering out high frequency variability it is difficult to attribute any differences to processes acting on a certain time scale. Studying differences in the precursors of their genesis on a multidecadal scale could give insight into their importance without observing the actual waves, but this would require more knowledge on their role in the Sahel rainfall. Currently there is uncertainty in the relationship between rainfall and wave activity, with recent studies suggesting a feedback relationship where convection modulate waves which then modulate convection, indicating a more complex relationship than previously understood (Gu et al., 2004; Nicholson, 2009).

The mismatch between the multidecadal Sahel rainfall in the CRU observational and ERA20C reanalysis datasets makes it difficult to draw statistical conclusions on the relationship between the multidecadal Sahel rainfall and North Atlantic SST variability within the ERA20C dataset as the statistical link is missing in the ERA20C dataset, even though the rainfall still exhibits a clear multidecadal variability over Sahel. Producing additional, dynamically consistent, reanalysis datasets with a higher correlation between the reanalysis and observational rainfall over Sahel on the multidecadal scale would enable further studies and a deeper insight into the causes for the dry/wet regimes and a more sound statistical basis for analysis. Model data with long time series and a good representation of the AMO pattern could also aid in investigating the multidecadal climate variability in the Sahel region and its relationship to the AMO.
4 Conclusion

The analysis of the Sahel rainfall and North Atlantic SSTs, based on the CRU and HadISST observational datasets, shows that there is a clear multidecadal variability in both regions with a period of 60-80 and 50-70 years respectively. The wet(dry) and warm(cold) periods are largely in phase, and both the global field correlation and the SVD analysis indicate a strong link between the multidecadal Sahel rainfall regimes and the AMO signal in the Atlantic. This result is consistent with previous results (Mohino et al., 2011; Zhang and Delworth, 2006; Folland, 1986).

The Sahel rainfall as characterized in the ERA20C reanalysis dataset also exhibits a clear multidecadal variability with a period of 60-80 years, although the wet/dry regimes are not in phase with the observations in CRU. However, the high correlation between the high-frequency CRU and ERA20C rainfall in Sahel indicates that the reanalysis dataset does capture the dynamics governing the inter-annual rainfall in the region.

The composites indicate that the strengthening(weakening) of the temperature induced meridional pressure gradient in the wet(dry) decades is the main cause of the multidecadal Sahel rainfall variability seen both in the observations and within the ERA20C reanalysis dataset. In the ERA20C reanalysis dataset the pressure gradient is strengthened over West Africa and both strengthened and shifted northward over East Africa in the wet decades compared to the dry, which accounts for the slight west-east difference in the dynamic response, i.e. the strengthening of the monsoon over West Africa and the northward shift of the monsoon features over East Africa.

The stronger meridional pressure and temperature gradients lead to an intensification of the different dynamical features connected the the West African Monsoon. The surface westerlies are intensified and extended higher up into the troposphere, bringing more moisture from the Tropical Atlantic in over the continent and further feeding the convective systems. The AEJ, which is induced by the thermal wind balance and strongly related to the strength and location of the meridional temperature gradient, is strengthened over West Africa and shifted northward over East Africa. The ascent region, which is located between the AEJ and TEJ axis, is shifted northward over East Africa and exhibits a general strengthening over all of Sahel, corresponding to the increase in rainfall in the same region. We can thus conclude that the change in meridional temperature and pressure gradients connected to the multidecadal rainfall variability results in both an increase(decrease) of moisture availability in the region and a strengthened(weakened) monsoon system, as well as a northward shift in the eastern region.

The observational datasets CRU and HadISST exhibit a clear correlation between the multidecadal rainfall variability in Sahel and the AMO, but this correlation is not present in the ERA20C reanalysis dataset due to the shift of the multidecadal wet and dry periods in Sahel within this dataset. This makes it difficult to draw conclusions on whether and how the AMO is affecting the Sahel rainfall using analysis from the ERA20C reanalysis dataset. A possible reason for this mismatch could be the lack of atmosphere-ocean coupling in the reanalysis model. Conducting research on fully coupled reanalysis and model products with long time series, such as the newly released CERA-20C reanalysis produced by ECMWF, could give insight into the atmospheric dynamics and hydroclimate in the tropics on a multidecadal scale and its relationship to the AMO.
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References


Supplement I: Significance of Horizontal Wind and Fluxes

Figure S1.1: Composite difference of the (a) zonal and (b) meridional wind at the 1000 hPa pressure level, 95% significance indicated with dashed lines.

Figure S1.2: Composite difference of the (a) zonal and (b) meridional wind at the 850 hPa pressure level, 95% significance indicated with dashed lines.
Figure S1.3: Composite difference of the (a) zonal and (b) meridional wind at the 550 hPa pressure level, 95% significance indicated with dashed lines.

Figure S1.4: Composite difference of the (a) zonal and (b) meridional wind at the 200 hPa pressure level, 95% significance indicated with dashed lines.

Figure S1.5: Composite difference of the (a) zonal and (b) meridional water vapour flux (vertical integral). 95% significance indicated with dashed lines.