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**EAST AFRICAN HYDROCLIMATE
VARIABILITY AND ITS INTERACTIONS
WITH THE INDIAN OCEAN OVER THE
LAST MILLENNIUM**

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LIST OF ABBREVIATIONS

AGCM	Atmospheric General Circulation Model
CMIP5	Coupled Model Intercomparison Project Phase 5
EMIC	Earth System Model of Intermediate Complexity
ENSO	El Niño-Southern Oscillation
EOF	Empirical Orthogonal Function
GCM	General Circulation Model
IOBM	Indian Ocean Basin Mode
IOD	Indian Ocean Dipole
IPCC	Intergovernmental Panel on Climate Change
ITCZ	Intertropical Convergence Zone
ONI	Oceanic Niño Index
NEMO	Nucleus for European Modelling of the Ocean
PMIP3	Paleoclimate Modelling Intercomparison Project Phase 3
SST	Sea Surface Temperature
TESSEL	Tiled ECMWF Scheme for Surface Exchanges over Land
UN	United Nations

CHAPTER 1

INTRODUCTION

1.1 General hydroclimate and topography of the study area

EAST Africa, as defined in this study, comprises the countries of Kenya, Tanzania, Somalia and Ethiopia. It is roughly located between latitudes 12°S and 10°N and longitudes 35°E and 50°E , with a particular focus here on the areas close to the Indian Ocean. In average, this region receives less rainfall than the other land surfaces of similar latitudes, which is due to a generally divergent large-scale atmospheric flow (Lyon, 2014). This makes it unique in the deep tropics (Yang et al., 2015). These overall dry conditions conceal, however, very wide variations between sectors (Fig. 1.1-a.). Some regions, as for instance much of the Horn of Africa, exhibit (semi-)desertic conditions with rainfall of less than 200 mm per year while others, such as the Ethiopian Highlands, are characterized by a very wet climate with rainfall above 2000 mm a year. One of the major factors driving this strong spatial heterogeneity is the complex topography (e.g. Hession and Moore, 2011), shown in Fig. 1.1-b.

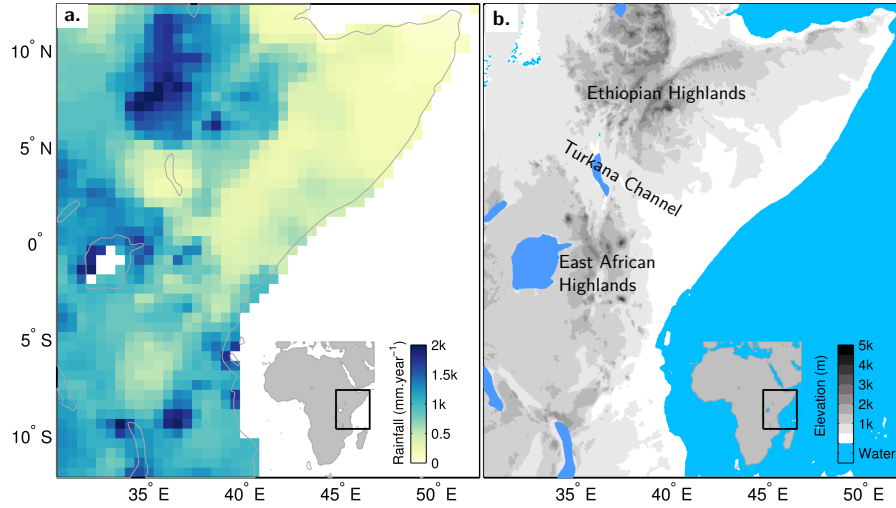


Figure 1.1 – a. Mean annual rainfall over land surfaces over the period 1901–2010 based on the data set GPCC-v7 (Schneider et al., 2014) and b. Topographic elevation in the study area from Amante and Eakins (2009).

The topography of East Africa consists essentially in a coastal plain in the east bounded on the west by highlands. The latter are closely related to the East African Rift, a zone characterized by a developing divergent tectonic plate boundary, in which the African Plate is in the process of splitting into two tectonic plates, called the Somali Plate and the Nubian Plate (e.g. Ebinger, 2005). The Ethiopian and the East African highlands are separated by a narrow gap, called the Turkana channel (Fig. 1.1-b), which routes southeasterly flow from over the Indian Ocean inland (Kinuthia, 1992). In addition to triggering considerable orographic rainfall, the East African topography thus also controls features of the local atmospheric circulation through the role played in the low-level wind patterns and moisture transport (e.g. Viste and Sorteberg, 2013). The spatial heterogeneity of the East African hydroclimate is reinforced by the presence of numerous lakes, primarily in the valley of the East African Rift. Those lakes are indeed recognized as important drivers of the East African regional climate system (e.g. Anyah et al., 2006), although their impact on atmospheric dynamics and the regional hydrological cycle remains poorly understood (Thiery et al., 2015).

The East African annual cycle of precipitation primarily depends on the seasonal migration of the Intertropical Convergence Zone (ITCZ) back and forth across the equator, following the apparent motion of the Sun. This meridional translation leads to a bimodal distribution of the cycle over much of the region, with a first rainy season occurring from March to May (the so-called long rains) and a second from October to December (short rains). The northward migration of the ITCZ is relatively slow and steady, bringing several weeks of heavy rainfall over the region during the long rains. In contrast, the southward migration in boreal autumn is more rapid and exhibits more variability, meaning that much of the interannual variability of the East African rainfall is controlled by the short rains (e.g. Nicholson, 1996; Mutai and Ward, 2000; Nicholson, 2014). The regions located further away from the equator, over the most southern and northwestern parts of the study area, are no more characterized by a bimodal cycle of rainfall but rather by a unimodal distribution, with a peak during austral and boreal summer, respectively (Owiti and Zhu, 2012; Yang et al., 2015).

1.2 Recent extreme meteorological events

Over the last few years, East Africa has been severely affected by both droughts and floods (Fig. 1.2). Coupled to geopolitical and socioeconomic factors such as poverty, conflicts, inflation or high population pressure, the humanitarian consequences of these extreme weather events are often dramatic for the local populations, the majority of whom being pastoralists and subsistence farmers. As mentioned in the fifth assessment report of the Intergovernmental Panel on Climate Change (IPCC), drought is a phenomena complex to define. It is however always related to a period of abnormally dry weather, which is long enough to cause a serious hydrological imbalance (Hartmann et al., 2013). In East Africa, droughts usually result in increased water shortages that lead to scarce pastures, reduced crop yields or even crop failures, and outbreaks of contagious livestock diseases. This ultimately induces mass migration and famine.

In 2005-2006, more than 11 million people were affected by critical food shortage in East Africa, due to severe drought coupled by the effects of conflicts (FAO, 2006). In 2008-2009, a widespread famine and humanitarian crises

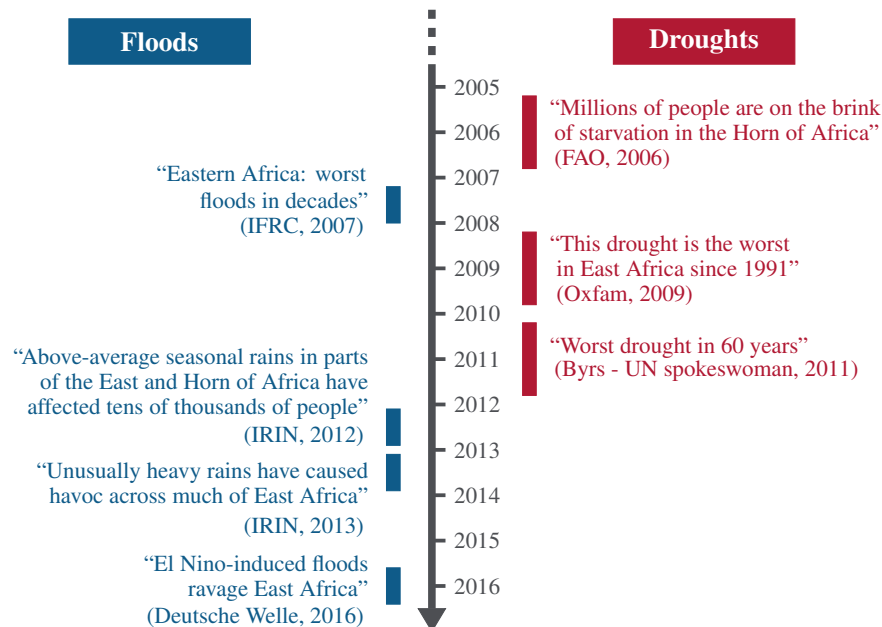


Figure 1.2 – Occurrence of floods and droughts having affected the East African region over the past ten years.

were caused by another drought (Mwangi et al., 2014), that affected 23 million East Africans (EMDAT, 2016). The drought that occurred in 2011-2012, sometimes said to be the worst in 60 years (Byrs, 2011), also led to a dire food security crisis in East Africa, affecting 13 million people (IFRC, 2011).

East Africa has also been impacted over the past few years by episodes of (flash) floods (Fig. 1.2). Paradoxically, the resulting humanitarian consequences, although more localized, are relatively similar, with soil erosion, damage to crops and infrastructures, and increases in human and livestock waterborne diseases. The effect of flooding are furthermore exacerbated in pastoral areas previously affected by droughts, where the absorption ability of the soil has become poor. In 2007, more than 650,000 East Africans lost their houses due to the worst floods in decades (IFRC, 2007). In 2012, tens of thousands people were again affected (IRIN, 2012) and in 2013, 225,000 people were displaced from their houses (OCHA, 2013). Finally, 2016 is character-

ized by heavy rainfall that has already wrecked havoc in several East African countries (Deutsche Welle, 2016; OCHA, 2016).

These extreme and opposite weather events underline the strong interannual variability of East African rainfalls. Understanding the processes driving these abnormally high/low rainfall is crucial to make accurate forecasts and for preparing adaptation or mitigation plans to these extreme meteorological events (e.g. Wilhite et al., 2014; Masih et al., 2014).

As already mentioned, the interannual variability of rainfall is dominated by the short rains. It is well established that rainfall during this season is linked to changes in sea-surface temperatures (SST) in the Pacific (e.g. Ropelewski and Halpert, 1987; Mutai et al., 1998; Indeje et al., 2000; Schreck and Semazzi, 2004; Hoell et al., 2014) and Indian (e.g. Hastenrath et al., 1993; Goddard and Graham, 1999; Hastenrath et al., 2007; Ummenhofer et al., 2009; Izumo et al., 2014) Oceans. Those SST changes are mainly related on the interannual time scale by two modes of variability that are described in the next section: El Niño-Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD). Consistently with this view, El Niño (La Niña) events often coincide with a high number of East African people affected by floods (droughts) (Fig. 1.3). For instance, the floods of 2007 and 2015-2016 were associated with El Niño events. Similarly, the droughts of 2008-2009 and 2010-2011 came with La Niña, as was the case for the most important drought in terms of affected people that occurred in 1999.

However, the coincidence between the phases of ENSO and extreme events in East Africa appears far from being systematic, as can be seen in Fig. 1.3. The link between ENSO, the IOD and the East African rainfall is actually complex, as explained in the following section.

1.3 Interannual variability of rainfall

ENSO is the most prominent mode of variability in the instrumental record (Schott et al., 2009). It originates in the tropical Pacific, but affects weather variability nearly worldwide, through atmospheric teleconnections. It is characterized by fluctuations between unusually high (El Niño) and low (La Niña) SSTs in the central and eastern equatorial Pacific, that occur every two to seven years (e.g. Cane, 2005; McPhaden et al., 2006). Typically, ENSO phases de-

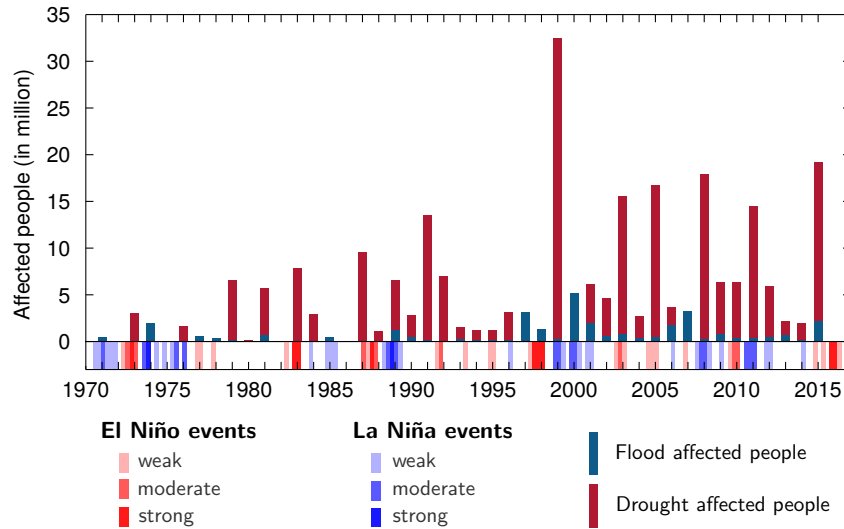


Figure 1.3 – Number of people affected by drought and flood in East Africa (EM-DAT, 2016), together with intensities of El Niño and La Niña events, based on the Oceanic Niño Index (ONI, http://www.cpc.noaa.gov/products/analysis_monitoring/ensostuff/ensoyears.shtml)

velop during boreal summer, peak during winter (corresponding to the East African short rains period) and decay the following spring (Xie et al., 2009).

Under neutral climatic state (neither El Niño nor La Niña), the trade winds tend to pile-up relatively warm waters in the western tropical Pacific Ocean, while the other side of the Ocean is affected by upwelling of relatively low SSTs. The warm pool at the west induces deep atmospheric convection and ascendant air motion, associated to low sea-level pressure. In the upper troposphere, the air returns eastward, and the loop is closed with sinking air motion over the cool eastern Pacific, leading to high pressure at the surface. This atmospheric circulation is referred to as the Walker circulation (e.g. Lau and Yang, 2002) (Fig. 1.4). It is associated to a positive feedback, called the Bjerknes feedback (Bjerknes, 1969). Indeed, the enhanced SST gradient caused by the winds leads to a reinforcement of the east-west sea-level air pressure difference across the basin, that in turn reinforces the winds.

During an El Niño event, the trade winds weaken while the gradient in atmospheric sea level pressure decreases. This leads to a shift of the warm

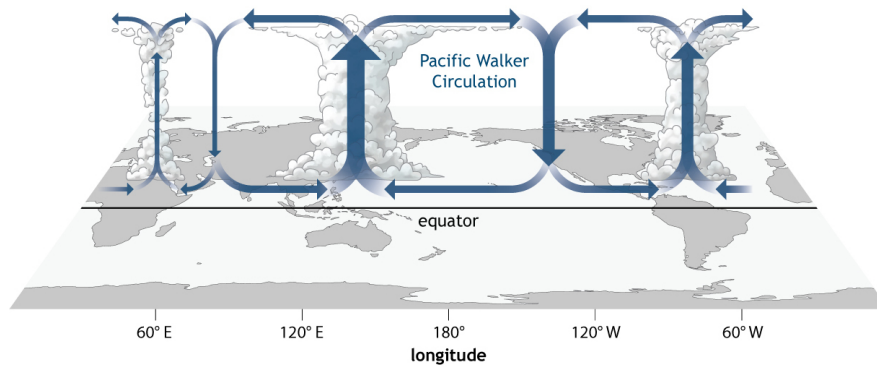


Figure 1.4 – Generalized Walker circulation under normal conditions (NOAA Climate.gov, drawing by Fiona Martin).

surface water eastward over the central to eastern equatorial Pacific, and thus of the atmospheric convection zone. Consequently, negative anomalies of SSTs and sea level are observed in the western Pacific (Wang and Fiedler, 2006). By contrast, La Niña refers to the situation when the Walker circulation is enhanced, with stronger gradient of SST and of sea level pressure between the eastern and the western tropical Pacific, the warm waters being then restricted in the latter area.

Although interannual variations in East African rainfall have been linked to ENSO (e.g. Mutai et al., 1998; Indeje et al., 2000; Mason and Goddard, 2001), several studies suggest that this relationship is the result of an indirect forcing of ENSO on the Indian Ocean (e.g. Goddard and Graham, 1999; Black et al., 2003; Black, 2005). Indeed, the phases of ENSO involve zonal displacements of the Walker circulation and variations of its strength, which affect the tropical Indian Ocean.

Previous observation-based studies have identified two dominant patterns of SST in the Indian basin associated with El Niño events, from empirical orthogonal function (EOF) analyses (Weare, 1979; Tourre and White, 1995). The first mode, that accounts for about 30-40% of the total variance, represents a basin-wide warming over the tropical Indian Ocean, that reaches a maximum in boreal spring, about one season after El Niño has peaked (Klein et al., 1999; Alexander et al., 2002). It is sometimes referred to as the Indian Ocean Basin Mode (IOBM; Yang et al., 2007). Much of the warming is attributed to a re-

duced cloud cover due to enhanced subsidence, leading to an increased incoming solar radiation over the eastern part of the ocean (Klein et al., 1999; Venzke et al., 2000; Alexander et al., 2002; Tokinaga and Tanimoto, 2004; Schott et al., 2009), which generates a gradual warming towards the western part of the basin (Xie et al., 2002; Jury and Huang, 2004; Schott et al., 2009). While this basin wide-warming appears robust, it does not seem to affect greatly the East African rainfall. Indeed, the teleconnection between interannual Indian Ocean SSTs and East African rainfall in boreal spring, roughly corresponding the long rains, is weak (e.g. Mutai and Ward, 2000; Pohl and Camberlin, 2006; Nicholson, 2014).

The second mode found in Weare (1979) accounts for about 10% of the variance. It displays a zonal SST dipole structure mostly dominant in boreal autumn, with a weak warming over the western Indian Ocean and abnormally cold SSTs in the East, off Java and Sumatra. This mode is now widely called the IOD (Saji et al., 1999; Webster et al., 1999). The IOD is, as ENSO, an interannual ocean-atmosphere coupled oscillation characterized by positive and negative phases. During the positive events, the SSTs are abnormally low in the southeastern Indian Ocean and abnormally high in the western Indian Ocean (Fig. 1.5). This pattern of SST is closely associated with changes in surface winds, the usually weak climatological equatorial westerlies over the tropical Indian Ocean being replaced by easterly winds (Webster et al., 1999). This produces upwelling and evaporative surface cooling off the west coasts of Java and Sumatra (Behera et al., 1999; Saji et al., 1999), while the thermocline becomes deeper in the western Indian Ocean, which increases SSTs (Webster et al., 1999; Yamagata et al., 2004). The resulting reversed SST gradient lead to a Bjerknes feedback which persists until the easterly wind stops, or remote forcing deepens the thermocline in the eastern Indian Ocean basin (Meyers et al., 2007).

The origin of this mode and its link with ENSO is controversial. Until the 1990s, the Indian Ocean interannual variability was mainly thought to be a rather passive response to the Pacific variability (e.g. Tourre and White, 1995; Latif and Barnett, 1995). In the late 90s, however, the IOD was first described as an inherent mode of variability of the Indian Ocean, since it can occur while the Pacific state is neutral (Saji et al., 1999; Webster et al., 1999). ENSO and IOD have thus been considered as independent climate modes. However, they often co-occur, the El Niño-induced SST pattern predisposing the Indian

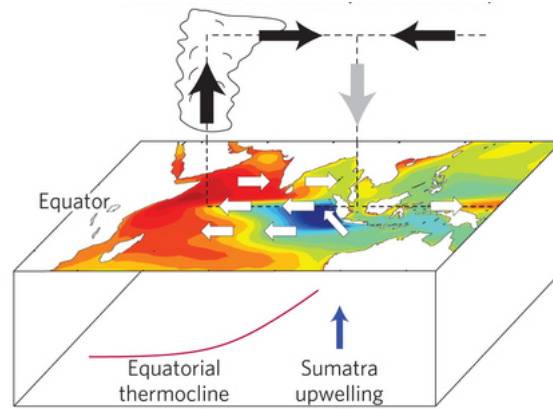


Figure 1.5 – Typical patterns of SSTs and surface winds, mean position of convection, and thermocline during a positive phase of the IOD (Figure from Cai et al., 2013).

Ocean to a positive phase of the IOD (Li et al., 2003; Black et al., 2003; Yamagata et al., 2004; Meyers et al., 2007; Schott et al., 2009).

The positive phases of the IOD are accompanied by enhanced short rains over East Africa. Indeed, the westwards low-level wind induced by the higher western Indian SSTs leads to a moisture flux convergence over the region (e.g. Clark et al., 2003; Black et al., 2003; Ummenhofer et al., 2009; Bahaga et al., 2015). By contrast, the negative events of the IOD are generally associated with abnormally low rainfall in East Africa (e.g. Hastenrath et al., 2004, 2007). Thanks to this relationship, the short rains can, to some extent, be predicted. For instance, the failure of the short rains in 2010, that initiated a major drought in 2011 in East Africa, was forecasted a few months in advance (Dutra et al., 2013). However, the drought has much worsened due to the subsequent failure of the long rains (Lyon and DeWitt, 2012), whose predictability is lower (Mwangi et al., 2014), or even nil (Funk et al., 2014). This long rains failure is actually part of a long-term decline observed from 1999 (Lyon and DeWitt, 2012) or even earlier (Funk et al., 2008), which raises the question whether it is linked to anthropogenic forcing or not (Lyon and DeWitt, 2012).

1.4 Current and future hydroclimate trends in East Africa

If the observed decline in the long rains is caused by anthropogenic forcing, one would expect East Africa to continue drying, as suggested in Williams and Funk (2011). However, there is no consensus about the causes of the observed decline in the long rains. Funk et al. (2008), Williams and Funk (2011) and Funk et al. (2014) attribute it to a general increase in the Indian Ocean SST, induced by anthropogenic emissions of well-mixed greenhouse gases, that triggers the westward extension of the warm pool over the Indian Ocean, while it is normally restricted to the western Pacific. This is accompanied by an extension of the Walker circulation, which results in subsidence motions and drying over East Africa. In contrast, Lyon and DeWitt (2012), Lyon (2014) and Yang et al. (2014) have linked the decline in the long rains to changes in the Pacific SSTs, namely to a La Niña-like pattern, with higher SSTs over the western tropical Pacific and lower ones over the central and eastern tropical Pacific. These changes are thought to be part of the natural multidecadal variability in Lyon (2014) and Yang et al. (2014).

Whatever the reason, this trend towards a drier climate in East Africa is at the opposite of most climate models projections, but not all of them (Conway et al., 2007; Otieno and Anyah, 2013), that show an increasingly wetter climate during the current century associated to anthropogenic forcing (e.g. Shongwe et al., 2011; Yang et al., 2014). Shongwe et al. (2011) showed that, in addition to an expected differential warming of the Indian Ocean producing a positive phase of the IOD-like pattern, which enhances the short rains, the models simulate a weakening of the climatological subsidence over eastern Kenya during the 21st century, associated with increased rainfall. This weakening of the Walker circulation is supported by other model-based studies (McHugh, 2006; Kirtman et al., 2013), and has already been observed since the mid-19th century (Vecchi et al., 2006). However, there is no general consensus in the observation-based studies, since Compo and Sardeshmukh (2010) and L'Heureux et al. (2013) suggested a strengthening of the Walker circulation over the twentieth century.

This contrast between observed decline and simulated increased of the long rains is sometimes referred to as the East African climate paradox (Rowell

et al., 2015). The inability of the General Circulation Models (GCMs) to reproduce the downward trend could be due to model error representing the forced change, potentially related to a biased representation of convection and cloud processes. The simulation of these processes is indeed still one of the main source of uncertainties in climate models (Flato et al., 2013), while most of the East African rainfall arises from local convection, rather than from synoptic-scale flows (Yang et al., 2015). This is related to the complex role of clouds to the climate system but also to the GCM spatial and temporal resolution. It is far too coarse to adequately represent explicitly the convective cells, which plays an important role in climate feedbacks and regional to global climate change (e.g. Zhang and Song, 2016). This thus requires the use of the parametrization of their effect, which is a long standing source of uncertainty (Flato et al., 2013).

The mismatch between observed and simulated hydroclimate over the last decades may also be legitimate if the observed trend is part of natural variability, as suggested in Yang et al. (2014) or in Lyon (2014). However, the most recent study of Rowell et al. (2015) found that this trend is likely not mostly driven by natural variability, although it may have contributed, while the study stays open regarding the role of model errors. In this context, it is thus crucial to assess the performance of GCM in simulating the East African hydroclimate.

1.5 East African hydroclimate in climate models

The most logical way for assessing the GCM performance in simulating the East african hydroclimate is to compare their results with instrumental datasets or reanalyses. This has been achieved in several studies (e.g. Conway et al., 2007; Anyah and Qiu, 2012; Otieno and Anyah, 2012; Yang et al., 2014; Rowell, 2013; Rowell et al., 2015). The overall conclusion which emerges is that most GCMs can simulate a bimodal distribution of seasonal rainfall as observed in the equatorial eastern Africa, but the cycle is misrepresented. The long rains are underestimated, and their peak occurs in May instead of April. In contrast, the short rains are overestimated, which might be linked to higher western Indian Ocean SSTs in the model compared to observations (Yang et al., 2015). These characteristics were observed with the Coupled Model

Intercomparison Project phase 3 (CMIP3) models (Anyah and Qiu, 2012), and persist with the subsequent generation, the CMIP5 models (Otieno and Anyah, 2012; Yang et al., 2014).

It is also important for the models to simulate well the teleconnections between the East African rainfall and the Indian and Pacific Oceans SSTs, which are the main driver of the interannual variability (e.g. Nicholson, 1996; Liebmann et al., 2014). The resulting SST anomaly pattern is strongly model-dependent, and has often large discrepancies with observations (Rowell, 2013; Yang et al., 2014). Once again, no improvement is brought by using CMIP5 models rather than CMIP3 ones for this diagnostic (Rowell, 2013). As already mentioned, the observed decline in long rains is not simulated by most models that show a wide variety of trends (Rowell et al., 2015). However, if the SSTs are prescribed, some models have a reasonable skill in predicting the long rains variability (Funk et al., 2014) and a good skill in reproducing the East African short rains variability (Bahaga et al., 2015). In general, the performance of current GCMs in simulating the East African hydroclimate and its link to the large scale SSTs is therefore very limited, which leads Otieno and Anyah (2012) and Yang et al. (2014) to conclude that the projections of these models have to be considered with caution.

The above mentioned studies are based on the comparison between model results and instrumental datasets. However, the latter only cover a few decades, which does not allow taking into account the (multi-)decadal variability of the East African climate. Yet it is thought to be an important component of the regional climate dynamics (Verschuren, 2004; Tierney et al., 2013), as suggested by the current downward trend of the long rains. This underlines the importance of assessing climate models over longer periods.

1.6 Objectives and outline of the thesis

Climate models struggle at simulating the seasonal cycle, recent trends and large-scale teleconnections of the East African rainfall. Furthermore, to our knowledge, they have never been assessed over longer period than the instrumental one, meaning that their ability to simulate long-term climate variability is unknown. This strongly hampers the reliability of climate projections in the region, while they are particularly needed for preparing mitigation and atten-

uation plans to extreme events that severely affect local populations. In this context, the overarching scientific question that is addressed in this thesis is the following:

How the East African rainfall is linked to the Indian Ocean SSTs at the interannual to the multi-decadal time scale?

It is answered through the development of three points, that will be used to structure the conclusion of this thesis:

1. Improving understanding of the link between the East African rainfall and Indian Ocean SSTs and of the underlying mechanisms.
2. Assessing the ability of the state-of-the-art GCMs in simulating the link between the East African rainfall and Indian SSTs, and the East African hydroclimate variations over the last millennium.
3. Investigating the potential interest of using the link between the East African rainfall and Indian SSTs to obtain better reconstructions of both variables during the last millennium.

Specifically, the thesis is structured as follows. **Chapter 2** focuses on the performance of climate models in simulating hydroclimate changes over the last millennium. A particular attention is given to distinguish the role played by the external forcings and by internal variability in the model results. The impact of the forcings on the last millennium teleconnections between the East African hydroclimate and the tropical Indian and Pacific SSTs is also investigated. The last millennium appears to be a good compromise between the availability of sufficient materials - both model results and proxy data - and a long enough period to account for low frequency hydroclimate variability. Unfortunately, the East African region is not conducive to the formation of archives allowing the reconstruction of past climate changes, the three traditionally ones being tree rings, ice cores and speleothems (Verschuren, 2003). Indeed, very few East African trees develop distinct annual rings, ice cores are only available on Mount Kilimanjaro and known high-quality speleothems are mainly restricted to Africa's extra-tropical north and south (Verschuren, 2003). In contrast, some of the many East African lakes contain accumulations of sediments that show great potential to document past climate change. Hence, all

hydroclimate proxy records available from eastern Africa that meet the criteria necessary for a meaningful model data comparison, ie. that are well dated and that have a sufficient time resolution, are based on lake-sediment records (Verschuren, 2004). In our analysis, we selected four proxy records that describe the water-balance history of Lake Challa and Lake Naivasha in eastern equatorial Africa, and of Lake Masoko and Lake Malawi in southeastern (but still inter-tropical) Africa. These reconstructions are part of the East African hydroclimate synthesis achieved in Tierney et al. (2013).

The last millennium is also covered by several model simulations. The period 850–1850 AD is indeed a target of the Paleoclimate Modelling Intercomparison Project Phase 3 (PMIP3; Otto-Bliesner et al., 2009), while the period 1850–2005 is a key period of the Coupled Model Intercomparison Project Phase 5 (CMIP5; Taylor et al., 2012). These projects aim at obtaining coordinated model experiments by providing a precise framework under which the model simulations have to be performed. One of the main tasks of PMIP3 and CMIP5 is to provide the climate forcing for the different periods selected (Schmidt et al., 2012). Some Earth System Models of Intermediate Complexity (EMICs), such as LOVECLIM (Goosse et al., 2010), have provided experiments for both PMIP3 and CMIP5. These models include simplifications and parametrisations of some physical processes, which allows enhancing computational efficiency. However, given the complexity of hydroclimate-related processes (e.g. Flato et al., 2013), we only focus on the simulations performed with the most sophisticated models available, the GCMs.

Before comparing model results to the last millennium reconstructions, the models are first tested against recent instrumental gridded datasets to assess their biases in the mean state and seasonal cycle. Although similar analyses have been performed previously (Section 1.5), it is important to repeat them here focusing specifically on the areas where the four record sites are located, with the models we use. Indeed, the conclusions of the studies assessing the performance of climate models during the recent past over East Africa are very sensitive to the model selected, but also to the study area and the variable considered.

The reliability of the gridded precipitation products over East Africa has been questioned (e.g. Otieno and Anyah, 2012). These products are mainly based on rain-gauge stations, but the number of these stations is weak in the region. The resulting observations thus suffer from an uneven spatial distribu-

tion, but also from gaps in time due to maintenance issues (e.g. Dinku et al., 2007; Sylla et al., 2013). To take these uncertainties into account, we use various gridded datasets, some of them also being based on model results and on satellite-induced data.

In **Chapter 3**, we investigate the potential of using the covariance that exists between East African rainfall and Indian Ocean SSTs to obtain better reconstructions of both variables over the last millennium. The link between these variables is well established, and Bahaga et al. (2015) have shown that there is a substantial skill in reproducing the recent East African short rains variability, as far as the SSTs are known. Improving the representation of a variable based on another by using their covariance can be particularly interesting over periods when instrumental observations are lacking and indirect proxy records are scarce, as is the case for the last millennium in East Africa. Here, this is achieved by means of a data assimilation method.

Climate models describe the evolution of many variables at any location and at any time, as a function of their spatial and temporal resolutions. However, using them alone does not allow knowing how realistic are the simulated results. The empirical information contained in proxy records gives an insight about the real climate, but the spatial distribution of East African hydroclimate-related proxy records covering the last millennium is scarce, as is the case for the Indian Ocean SST-related proxy records. Data assimilation is a technique which aims to combine the information from climate models and proxy records to find better estimates of past climates, that are consistent with the empirical information contained in proxy data, the model physics, and the forcings used to drive the model experiments. If such estimates are found, the proxy record information is propagated to other climate variables and spatially spread, using the dynamics of the climate model. Since the physics of the model is respected, the choice of the model used is critical. Here, we selected the Community Earth System Model version 1.1 (CESM1; Hurrell et al., 2013), that appears to simulate a realistic teleconnection between East African rainfall and Indian SSTs, as deduced from the comparison with recent observations (Chapter 2).

The East African hydroclimate data considered in the assimilation process are the same as the ones used in Chapter 2. Added to that, six SSTs-related records spread over the Indian Ocean are also used as constraints for the assimilation. The choice of these latter records is based on the study of Tierney et al. (2015), who compiled all published and publicly available marine

paleoclimate data sets derived exclusively from tropical coral archives. Data assimilation is still considered as relatively new in palaeoclimatology (Matsikaris et al., 2015). It has been used to investigate the consistency between proxy records and model results (e.g. Mairesse et al., 2013), or to study the processes responsible for past climate changes as recorded by proxy data (e.g. Crespin et al., 2009; Widmann et al., 2010; Goosse et al., 2011, 2012), but to our knowledge, it is the first time that it is used to reconstruct East African rainfall based on SSTs, and conversely, taking advantage of their covariance over the last millennium.

The existing covariance between East African rainfall and tropical Indian SSTs does not imply that these variables are dynamically linked, and the data assimilation method does not allow identifying directly the underlying processes. The vast majority of the studies dealing with the teleconnection between East African rainfall and tropical SSTs focuses on the existence of this link by means of statistical tools, such as correlation coefficients (e.g. Ogallo et al., 1988; Saji et al., 1999; Clark et al., 2003; Rowell, 2013; Klein et al., 2016; Schubert et al., 2016), empirical orthogonal functions (Schreck and Semazzi, 2004; Saji et al., 1999) and composite (Saji et al., 1999) or harmonic (Nicholson and Selato, 2000) analyses. Only a few studies (Goddard and Graham, 1999; Ummenhofer et al., 2009) have examined the processes responsible for this link, leading Lyon (2014) to conclude that more research is needed to better understand the physical processes associated with the rainfall variability in East Africa across multiple time scales.

In **Chapter 4**, we investigate whether the temperature dipole, ie. the gradient between the western and the eastern tropical Indian Ocean SSTs, is indeed the proximate cause of enhanced rainfall in East Africa, or whether the local warm SST anomalies are sufficient to induce the increased rainfall, while the eastern cold pole is of lesser importance, as suggested in Ummenhofer et al. (2009). This is achieved through the analyses of two sensitivity experiments performed with the GCM EC-EARTH (Hazeleger et al., 2012). In the first experiment, the western Indian Ocean surface is warmed by a constant artificial flux of 100 W.m^{-2} while in the second one, the same area is still warmed but to a lesser extent by a flux of 50 W.m^{-2} , and the eastern Indian Ocean surface is cooled by a flux of -50 W.m^{-2} . In order to be confident with the results obtained, the choice of the model selected is crucial. EC-EARTH is well suited for our purpose, since it simulates very realistic teleconnections between East

African rainfall and Indian SSTs, as deduced from the comparison with recent instrumental datasets, while most GCMs fail to do so (Chapter 2). However, it could not be used in Chapter 2 because, to our knowledge, there is no simulation covering the last millennium performed with this model.

The general conclusions, the main contributions as well as some perspectives of this thesis are discussed in **Chapter 5**.

Finally, due to reasons related to my employment contract, the first year of my thesis has been dedicated to the study of the Arctic sea ice at the mid-Holocene. This work has lead to an article published in the peer-reviewed journal *Climate of the Past* (see Klein et al., 2014). Although it has used similar methodologies than the ones used here, including model-data comparison and data assimilation analyses, it is not included in this thesis given the quite different topic.

CHAPTER

COMPARISON OF SIMULATED AND RECONSTRUCTED VARIATIONS IN EAST AFRICAN HYDROCLIMATE OVER THE LAST MILLENNIUM

This chapter is based on the following published article:

Klein, F., Goosse, H., Graham, N. E. and Verschuren, D. (2016). Comparison of simulated and reconstructed variations in East African hydroclimate over the last millennium. *Climate of the Past*, **10**(7), 1499–1518.

Abstract

The multi-decadal to centennial hydroclimate changes in East Africa over the last millennium are studied by comparing the results of forced transient simulations by six General Circulation Models (GCMs) with published hydroclimate reconstructions from four lakes: Challa

and Naivasha in equatorial East Africa, and Masoko and Malawi in southeastern inter-tropical Africa. All GCMs simulate fairly well the unimodal seasonal cycle of precipitation in the Masoko/Malawi region, while the bimodal seasonal cycle characterizing the Challa/Naivasha region is generally less well captured by most models. Model results and lake-based hydroclimate reconstructions display very different temporal patterns over the last millennium. Additionally, there is no common signal among the model time series, at least until 1850. This suggests that simulated hydroclimate fluctuations are mostly driven by internal variability rather than by external forcing. After 1850, half of the models simulate a relatively clear response to forcing, the main one being the anthropogenic forcing, but this response is different between the models. Overall, the link between precipitation and tropical sea surface temperatures (SSTs) over the pre-industrial portion of the last millennium is stronger and more robust for the Challa/Naivasha region than for the Masoko/Malawi region. At the inter-annual time scale, last-millennium Challa/Naivasha precipitation is positively (negatively) correlated with western (eastern) Indian Ocean SST, while the influence of the Pacific Ocean appears weak and unclear. Although most often not significant, the same pattern of correlation between East African rainfall and the Indian Ocean SST is still visible when using the last-millennium time series smoothed to highlight centennial variability, but only in fixed-forcing simulations. This means that, at the centennial time scale, the effect of (natural) climate forcing can mask the imprint of internal climate variability in large-scale tele-connections.

2.1 Introduction

IN 2011, the Horn of Africa was affected by the most serious drought in decades, leading to severe humanitarian consequences including food and water shortages, acute malnutrition, mass displacement and conflicts (OCHA, 2011; Hillbruner and Moloney, 2012). This drought was followed the next two years by strong pluvial events that triggered floods in Kenya and some parts of Somalia (OCHA, 2012; IFRC, 2013a,b). These consecutive and opposite extreme events illustrate the strong inter-annual variability characterizing the East African rainfall (e.g. Nicholson et al., 2012). Due to the seasonal migration of the Intertropical Convergence Zone (ITCZ) back and forth across the equator, rainfall over a major portion of East Africa has a bimodal annual cycle with a main rainy season during March-May (often referred as long rains) and a weaker rainy season during October-December (often referred as short rains) (e.g. Yang et al., 2015). The short rains are more variable from one year to another, and thus drive most of the observed inter-annual variability (e.g. Hastenrath et al., 1993; Nicholson, 1996, 2014). Numerous studies have emphasized the tele-connection between the East African short rains and either the El Niño/Southern Oscillation (ENSO, e.g. Ogallo et al., 1988; Hastenrath et al., 1993; Nicholson and Selato, 2000; Schreck and Semazzi, 2004; Hoell et al., 2014) or the Indian Ocean Dipole (IOD, e.g. Goddard and Graham, 1999; Saji et al., 1999; Webster et al., 1999; Clark et al., 2003; Ummenhofer et al., 2009; Izumo et al., 2014). However, the mechanisms involved are less clear. Goddard and Graham (1999) and Ummenhofer et al. (2009) suggested that an ocean driven change to the atmospheric Walker circulation impacts East African rainfall, while Klein et al. (1999) mentioned an atmosphere driven change affecting both SSTs and rainfall. In any case, the 2011 drought was triggered by a strong La Niña event (IRI, 2010; Hoell et al., 2014) associated with a negative IOD (JAMSTEC, 2015) that resulted in drier than normal conditions in East Africa during the short rains at the end of 2010. The drought then worsened due to subsequent failure of the long rains in 2011 (Lyon and DeWitt, 2012).

Unlike short rains, the tele-connection between inter-annual East African long rains and the Indian and Pacific oceans is generally considered to be weak (e.g. Mutai and Ward, 2000; Pohl and Camberlin, 2006; Nicholson, 2014). However, failure of the long rains in 2011 was part of a progressive decline

in long rains that has started around 1999 (Lyon and DeWitt, 2012) or even earlier (Funk et al., 2008), was associated with abrupt warming of the Indian Ocean (Funk et al., 2008; Williams and Funk, 2011) or of the western tropical Pacific (Merrifield, 2011; Lyon and DeWitt, 2012), also altering the Walker circulation. Merrifield (2011) and Lyon and DeWitt (2012) do not propose a specific cause for this warming. By contrast, Funk et al. (2008) and Williams and Funk (2011) attribute the large-scale shift in Indian Ocean SSTs to anthropogenic forcing, and suggest that a warmer future climate will bring an increased frequency of drought conditions in tropical eastern Africa owing to further reductions in the long rains.

This hypothesis is at odds with general circulation models (GCMs) showing that a warmer climate is associated with an increase in precipitation minus evaporation (P-E) in the intertropical convergence zone (ITCZ), including the East African long rains (Seager et al., 2010; Laîné et al., 2014). Other model-based studies (McHugh, 2005; Shongwe et al., 2011; Kirtman et al., 2013) furthermore suggest that increasingly wetter rainy seasons in East Africa are due to a weakening of the Walker circulation, likely linked to anthropogenic warming (Vecchi et al., 2006; Vecchi and Soden, 2007). This is corroborated by some observations which appear to show a weakening of the Walker circulation already since the mid-19th century (Vecchi et al., 2006). However, there is no agreement on that in observation-based studies, as illustrated by L'Heureux et al. (2013) who found a multi-decadal strengthening of the Walker circulation over the same period. In addition, some regional climate models forced at the boundaries by ensemble-mean GCM results are not consistent with GCMs in that they show a reduction rather than increase in the long rains (Vizy and Cook, 2012; Cook and Vizy, 2013).

The inability of the GCMs in simulating the observed recent downward trend of the long rains implies either that it is part of (multi-)decadal natural variability (Lyon and DeWitt, 2012; Yang et al., 2014; Lyon, 2014), or that the GCMs inadequately represent the climate processes occurring in the region and the response to anthropogenic forcing. In this context, it is crucial to assess the performance of GCMs in simulating East African rainfall. Existing studies on this subject (e.g. Conway et al., 2007; Anyah and Qiu, 2012; Otieno and Anyah, 2012; Yang et al., 2014) have reached contrasting conclusions depending on the region or spatial scale, or on the variables and models considered. Specifically, they showed that the mean seasonal cycle of precipi-

tation is reasonably well simulated by the majority of GCMs, but that there is a large spread among them in capturing the actual dominant peaks where rainfall is bimodal (Anyah and Qiu, 2012; Otieno and Anyah, 2012). Additionally, most models appear to have significant biases in monthly mean precipitation, and the observed link between the East African rainfall and the Indian Ocean SST is often not well represented (Conway et al., 2007; Yang et al., 2014).

All the above studies are limited to the recent past where direct measurements of precipitation exist. However, the period considered, which ranges from the last few decades to 150 years at most, is not sufficient to capture the multi-decadal variability that is thought to be an important component of East African hydroclimate (Verschuren, 2004; Tierney et al., 2013). Therefore, to complement those studies, our goal is to extend this analysis to the last millennium by analyzing proxy records of past hydroclimatic change over this period in conjunction with simulations performed in the framework of the third phase of the Paleoclimate Modelling Intercomparison Project (PMIP3; Otto-Bliesner et al., 2009) and of the fifth phase of Coupled Model Intercomparison Project (CMIP5; Taylor et al., 2012). All hydroclimate proxy records available from eastern Africa that are both well-dated and span the last millennium with sufficient time resolution are based on lake-sediment records (Verschuren, 2004). In this study, we consider proxy records describing the water-balance history of four East African lakes: Lake Challa and Lake Naivasha in eastern equatorial Africa, and Lake Masoko and Lake Malawi in southeastern (but still inter-tropical) Africa (Fig. 2.1). These four lake records are part of the East African hydroclimate synthesis recently achieved by Tierney et al. (2013), and are all characterized by strong multi-decadal to centennial variability. As a consequence, the present study focuses on relatively long-term hydroclimate changes, and on variation in annual means rather than individual rainy seasons, in contrast with model and observation-based studies about variation in recent East African rainfall (e.g. Anyah and Qiu, 2012; Yang et al., 2014).

Specifically, our study analyzes GCM simulations of long-term hydroclimate change relative to reconstructions over the last millennium to define whether the simulated changes reflect the forcing of external climate drivers and to assess the stability of large-scale tele-connections between East African rainfall and global SSTs. This paper is structured as follows. In Section 2.2, we introduce the model experiments and proxy-based reconstructions. In Section 2.3, we evaluate the comparative performance of six different GCMs to simu-

late the seasonal cycle of rainfall over the study regions and its tele-connection to tropical SSTs over the recent period. In Section 2.4 we analyze the results of model simulations spanning the last millennium. The contribution of forced and internal variability on those simulated hydroclimate changes and the stability of large-scale tele-connections are finally investigated in Section 2.5, followed by a discussion and conclusions in Section 2.6.

2.2 Data and methods

2.2.1 PMIP3/CMIP5 model experiments

Climate model simulations from PMIP3 (Otto-Bliesner et al., 2009) and CMIP5 experiments (Taylor et al., 2012) were obtained from the Program for Climate Model Diagnosis and Inter-comparison (PCMDI; <http://pcmdi9.llnl.gov>) and the Earth System Grid (www.earthsystemgrid.org) archives. The six GCMs selected (Table 2.1) are those for which the diagnostic variables of interest, i.e. precipitation, actual evaporation and SST, were available at the time of our analysis, for both *past1000* (850–1850 AD) and *historical* (1850–2005) periods, as well as for *pre-industrial control* runs.

Table 2.1 – Modeling centers, parameters and references of the PMIP3/CMIP5 models used in this study.

Model name	Institution	Resolution (lat*lon)		Ensemble members		Reference
		Ocean	Atm.	past1000	historical	
CCSM4	National Center for Atmospheric Research	384*320	192*288	1	6	Landrum et al. (2013)
CESM1	National Center for Atmospheric Research	384*320	96*144	10	10	Otto-Bliesner et al. (2015)
GISS-E2-R	NASA Goddard Institute for Space Studies	90*144	90*144	1	6	Schmidt et al. (2014)
IPSL-CM5A-LR	Institut Pierre-Simon Laplace	149*182	96*96	1	5	Dufresne et al. (2013)
MPI-ESM-P	Max Planck Institute for Meteorology	220*256	96*192	1	2	Giorgetta et al. (2013)
BCC-CSM1-1	Beijing Climate Center, China Meteorological Administration	232*360	64*128	1	3	Wu et al. (2014)

Although not continuous, except for CESM1 and MPI-ESM-P, the first ensemble members (r1i1p1) of *past1000* runs were merged with the corresponding *historical* simulations to obtain results spanning the period 850–2005 AD.

The impact of the discontinuity is probably limited since it falls within the range of internal climate variability for surface variables in all cases. The simulations are driven through the last millennium by both natural (orbital, solar, volcanic) and anthropogenic (well-mixed greenhouse gases, ozone, tropospheric aerosols, land use) climate forcings. Earth's orbital parameters vary according to the calculations of Berger (1978). Depending on the model, different reconstructions of solar irradiance variability are applied. All models except, CESM1 and GISS-E2-R, use the reconstruction by Vieira and Solanki (2009) from 850 to 1609 and by Wang et al. (2005) from 1610 to 2005. CESM1 uses the reconstruction by Vieira et al. (2011) with the spectral variations and '11-year' solar cycle from Schmidt et al. (2012), whereas GISS-E2-R uses the Steinhilber et al. (2009) reconstruction until 1849 and the Wang et al. (2005) one from 1850 onwards.

The forcing related to volcanic aerosols is derived from Crowley and Unterman (2013) in GISS-E2-R, and MPI-ESM-P and from Gao et al. (2008) in the four other GCMs. Reconstructed and observed changes in the major greenhouse gases driving *past1000* (Flückiger et al., 2002; MacFarling Meure et al., 2006) and *historical* (Hansen and Sato, 2004) simulations, ie. CO₂, CH₄ and N₂O, are the same in all models. Anthropogenic changes in land use/land cover over the last millennium are based on the reconstruction of Pongratz et al. (2008) in MPI-ESM-P, of Pongratz et al. (2008) followed by the reconstruction of Klein Goldewijk and van Drecht (2006) for the historical period in GISS-E2-R and of Pongratz et al. (2009) followed by the reconstruction of Hurtt et al. (2011) for historical time in CCSM4 and CESM1. BCC-CSM1-1 and IPSL-CM5A-LR do not consider any change in land use/land cover, whose distribution is fixed to the pre-industrial value. Tropospheric ozone and aerosols variations are also taken into account in *historical* experiments in CCSM4, CESM1, GISS-E2-R, MPI-ESM-P and BCC-CSM1-1, and are all based on the dataset described in Lamarque et al. (2010). These changes are however neglected in IPSL-CM5A-LR, which considers a constant concentration fixed at the pre-industrial level. More information on the climate-forcing reconstructions used to drive *past1000* experiments and on their implementation can be found in Schmidt et al. (2011) and Schmidt et al. (2012).

2.2.2 Proxy-based hydroclimate reconstructions

Despite the relatively large number of lakes present across East Africa, only a small sub-set of them combine continuous sedimentation (and thus, archiving) with hydrological sensitivity to climatic moisture-balance changes (Verschuren, 2003). Recently, Tierney et al. (2013) selected seven East African proxy records that are well-dated and meet the criteria of primarily reflecting hydroclimate variation and of covering the last millennium with a time resolution better than 50 years. Our present study focuses on four of these records, originating from Lake Challa, Lake Naivasha, Lake Masoko and Lake Malawi. The records from Lake Tanganyika and Lake Edward are not considered because they are located far from the Indian Ocean and thus to the west of our region of interest. The record from Lake Victoria is not considered because the representation of this large lake varies from one model to another, which precludes a meaningful comparison between model results and proxy records for this site. Indeed, while most GCMs ignore its presence, the MPI-ESM-P model specifically recognizes it as a surface-water body surrounded by continent. It is well known that Lake Victoria itself strongly influences the regional hydrological cycle (e.g. Thiery et al., 2015), but those effects cannot be adequately reproduced in GCMs with relatively coarse spatial resolution. Several other proxy records exist which describe East African hydroclimate variability during the last millennium (Verschuren, 2004, see also <http://t1p.de/mwp>). The majority of these mostly lake-based records do not possess sufficient age control to assess the regional coherence of (multi-) decadal and century-scale hydroclimate variations. Since our goal here is not to extensively review the strengths and weaknesses of those individual reconstructions, we follow Tierney et al. (2013) to consider only the handful of records that do meet minimum criteria of continuity and hydroclimate signal strength. However, a critical review of all available records might nevertheless refine the spatial structure of documented hydroclimate changes, and allow further assessment of the robustness of broad-ranging climate-dynamic inferences.

The 1000-year time series representing hydroclimate variation in the Lake Challa region developed by Tierney et al. (2013) is the first principal component of the composite variation in three moisture-balance proxies, namely the branched and isoprenoidal tetraether index BIT (a presumed indicator of total annual rainfall: Verschuren et al., 2009; Buckles et al., 2016); δD in the leaf

waxes of terrestrial plants (an isotopic proxy for rainfall source and intensity: Tierney et al., 2011); and varve thickness (a proxy for variation in dry-season length and windiness: Wolff et al., 2011). This first principal component accounts for 40% of the variance in the data (supplementary material of Tierney et al., 2013). The time series from Lake Naivasha is a lake-level reconstruction based on sediment lithostratigraphy (Verschuren, 2001), supported by salinity reconstructions based on fossil diatom and midge assemblages (Verschuren et al., 2000). The hydroclimate record from Lake Masoko is inferred from the low-field magnetic susceptibility of the sediment, which is a proxy for lake-level changes and/or wind stress. Two such records are available for this lake, one that goes back to -43,300 AD (Garcin et al., 2006) and one that starts around 1500 AD (Garcin et al., 2007). The Masoko time series in this paper is obtained from Tierney et al. (2013), who used the last millennium of the longer record but with age-depth tie-points translated from the shorter record (Anchukaitis and Tierney, 2013). Finally, the hydroclimate record from Lake Malawi is deduced from the mass accumulation rate of the terrigenous sediment fraction, presumed to be a runoff proxy (Brown and Johnson, 2005; Johnson and McCave, 2008). Table A1 provides more information about each of these four proxy records. Although these records are derived from different proxies, their time series can all be qualitatively viewed as smoothed versions of the local moisture-balance history of the corresponding sites.

2.3 Evaluation of model performance over the period 1979-2005

2.3.1 Mean seasonal cycle of precipitation

This section assesses the ability of various GCMs to reproduce the observed mean state and seasonal cycle of the East African rainfall. Although similar analyses have been performed previously (e.g. Conway et al., 2007; Anyah and Qiu, 2012; Otieno and Anyah, 2012; Yang et al., 2014), it is important to repeat it here focusing specifically on the areas where our four study sites are located (Fig. 2.1).

The number of rain-gauge stations in East Africa is small, and the observations suffer both from an uneven spatial distribution and from gaps in time

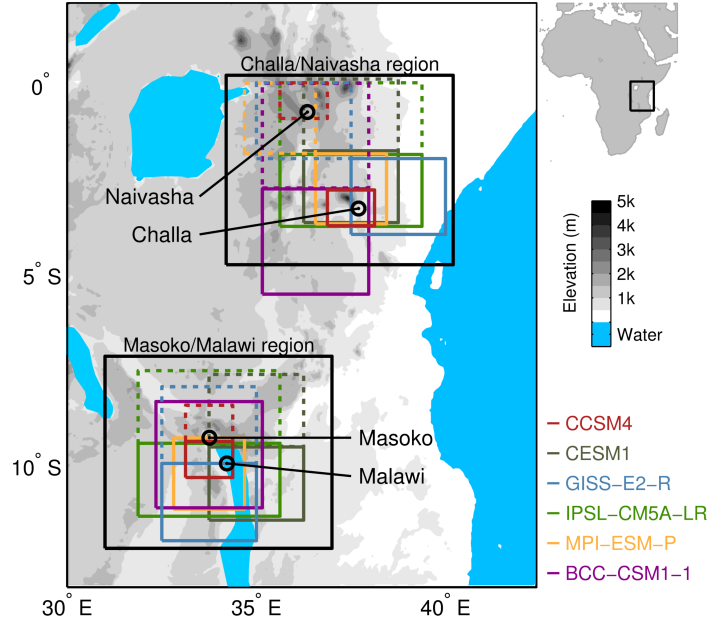


Figure 2.1 – Location of lakes Challa, Naivasha, Masoko and Malawi in East Africa, along with the individual grid cells containing each of these four sites in six different CMIP5 models (dashed (plain) boxes for the grid cells that contain the lakes Naivasha and Masoko (Challa and Malawi)), and the two larger regional domains over equatorial East Africa (Challa/Naivasha region) and southeastern inter-tropical Africa (Masoko/Malawi region). Topography from Amante and Eakins (2009).

due to maintenance issues (Dinku et al., 2007; Sylla et al., 2013). We have therefore used global gridded datasets that merge the information from rain-gauge stations, remote sensing, and/or reanalysis results. However, these gridded datasets have their own uncertainties, related for instance to the number and the treatment of rain-gauge measurements or of radar precipitation estimates (Otieno and Anyah, 2013). In order to estimate the effect of these uncertainties on our conclusions, we used four global monthly gridded datasets of precipitation. Version 6 of the Global Precipitation Climatology Centre data set (GPCC-v6; Schneider et al., 2014) is a reanalysis using rain-gauge data only. It spans the period from 1901 to the present with a spatial resolution of $0.5^\circ \times 0.5^\circ$. Version 2.2 of the Global Precipitation Climatology Project (GPCP-v2.2; Huffman et al., 2009) combines rain-gauge and satellite-based

precipitation data on a $2.5^{\circ} \times 2.5^{\circ}$ grid from 1979 to the present. The Climate Prediction Center (CPC) Merged Analysis of Precipitation data set (CMAP; Xie and Arkin, 1997) covers the same period at identical spatial resolution but combines rain-gauge data and different satellite estimates with NCEP/NCAR reanalysis results in gaps. Finally, NOAA's Precipitation Reconstruction over Land data set (PREC/L Chen et al., 2002) is based only on rain-gauge data and covers the period from 1948 to the present with a spatial resolution of $0.5^{\circ} \times 0.5^{\circ}$.

Due to the seasonal north-south migration of the ITCZ across the equator, the East African rainfall is characterized by a strong annual cycle that differs from one location to another (Nicholson, 1996; Otieno and Anyah, 2013; Yang et al., 2015). The seasonality of rainfall is bimodal over equatorial sites such as Lake Challa and Lake Naivasha, with two rainy seasons occurring in March to May (long rains) and in October-December (short rains), while it is unimodal in the southeastern lakes Masoko and Malawi, with a maximum between November and April during the austral summer (bar charts in Fig. 2.2). The observed mean monthly rainfall in each of the four study areas over the period 1979-2005 serves as our reference frame to compare the success of individual GCMs in simulating the present-day seasonal cycle, using model results from the individual grid cells which include the lakes (Fig. 2.1).

For Lake Naivasha (Fig. 2.2-a), simulated monthly mean precipitation is characterized by a large spread among models. Observed short rains over this lake are relatively well simulated by most models, except by GISS-E2-R and IPSL-CM5A-LR which respectively strongly overestimate and underestimate them. During the other seasons, the simulated precipitation over Lake Naivasha is underestimated by all models except GISS-E2-R, including during the main rainy season in boreal spring. Regarding the average of monthly mean precipitation throughout the year at Lake Challa (Fig. 2.2-b), three models are within the range of the observations: CCSM4, CESM1 and BCC-CSM1-1. Most models underestimate the long rains except CESM1 and GISS-E2-R, although in these two models, this rainy season is delayed by one month compared to observations. In contrast with the observations, all models show highest rainfall in October or November rather than April, but the spread is again large. These differences between models during the short rains are consistent with biases at larger spatial scales noted in previous studies of the East African region. Anyah and Qiu (2012) and Yang et al. (2014) indeed showed that, de-

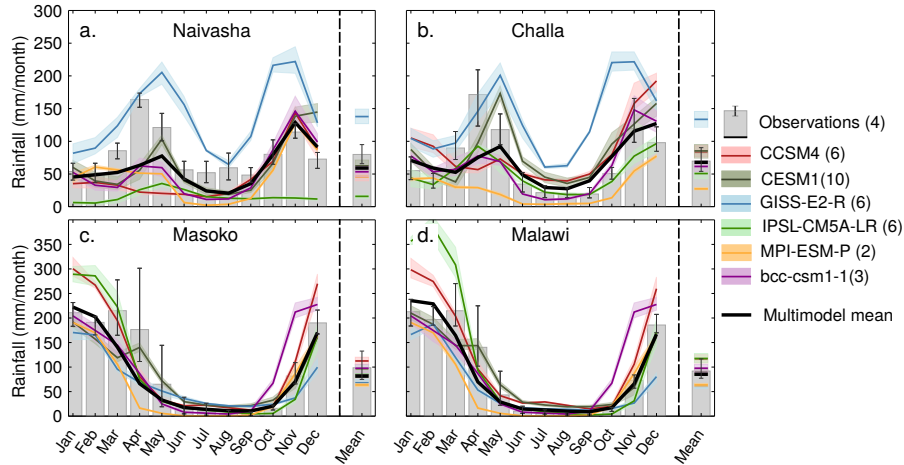


Figure 2.2 – Mean monthly rainfall over lakes Challa, Naivasha, Masoko and Malawi (a-d) in observations (bar plots) and in six CMIP5 models (curves) over the period 1979-2005. The number of datasets (for the observations) or ensemble members (for the models) used in each case is shown in brackets. Error bars and shaded areas represent the range of those observations or ensemble member values.

spite a large spread among CMIP3 and CMIP5 models, most of them tend to underestimate and to shift by one month the long rains, and to overestimate the short rains. Agreement among models and between models and observations is much higher in Lake Masoko and Malawi (Fig. 2.2-c and d). Both the rainy and dry seasons are well simulated, although the amount of rain is overestimated by CCSM4 and IPSL-CM5A-LR during the rainy season. Overall, the climate models used in this study are thus able to represent the unimodal rainfall seasonality characterizing the region encompassing lakes Masoko and Malawi, while the timing and the magnitude of the two rainy seasons characterizing the region encompassing lakes Challa and Naivasha are in general less well captured.

Comparing model results and data at individual grid cells can be questionable since model skill at this scale is often very limited. For instance, a small shift in the spatial structure of the simulations compared to the observations can lead to large difference in precipitation. Local topographic features not well represented at the grid scale may also have a significant impact. Besides, the surface areas of the grid cells which include the lake sites strongly dif-

fer from one model to another (Fig. 2.1). To get rid of the problems linked to differences in spatial resolution and to remove local noise in favour of more regional patterns, it seems better to analyze, instead of individual grid cells, larger regions presenting common characteristics as discussed in the next section.

2.3.2 Link between individual grid cells and the larger spatial domains selected for analysis

Lake Challa and Lake Naivasha on the one hand and Lake Masoko and Lake Malawi on the other have a very similar climatology and seasonal cycle in the recent period, both in models and observations (Fig. 2.2). We thus consider a spatial domain which includes the first two lakes (0.2° N to 4.8° S and 34.2° E to 40.2° E, referred to as the Challa/Naivasha region) and a second one which includes the last two (7.2° S to 12.2° S and 31° E to 37° E, referred to as the Masoko/Malawi region; Fig. 2.1). Note that shifting or changing the size of these two regions to some extent does not produce substantial changes in the results.

However, using larger grid boxes raises the issue of whether the proxy-based reconstructions that are compared to model results over the last millennium are representative of these larger spatial domains. Fig. 2.3 shows the correlation between modeled mean annual rainfall in the individual grid cells containing the four lake sites and the two larger domains defined for our analysis, for both the recent period and the last millennium. Changes in precipitation within the grid cell containing Lake Masoko, within the grid cell containing Lake Malawi and within the larger box representing the Masoko/Malawi region are highly and significantly correlated for all models and observations, and for both periods. the rainfall over Lake Challa, Lake Naivasha and the Challa/Naivasha region is also positively correlated in both periods for each source of information.

The observed recent rainfall over Lake Challa, Lake Naivasha, and the Challa/Naivasha region shows no or only a weakly positive relationship with rainfall over Lake Masoko, Lake Malawi and the Masoko/Malawi region, underscoring the climatic dichotomy characterizing East Africa. Note that no negative correlation is found except very weak ones in GISS-E2-R between rainfall over Lake Challa and rainfall over Lake Masoko, Lake Malawi and

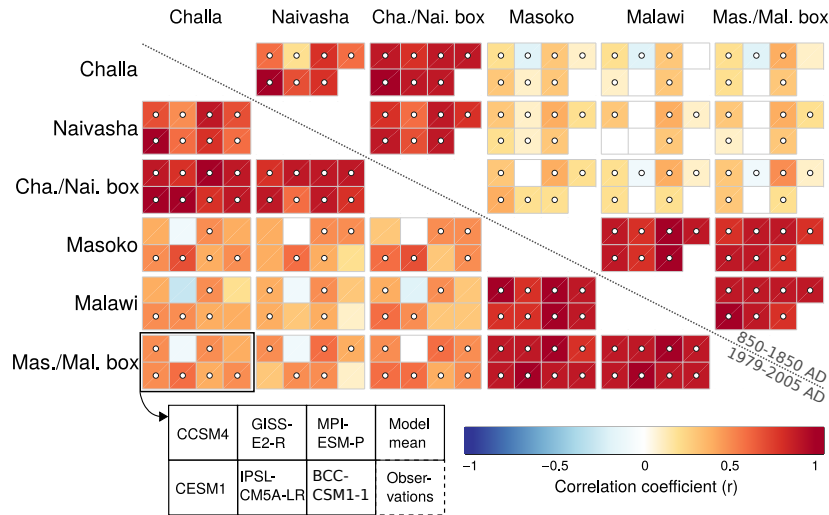


Figure 2.3 – Pearson correlation coefficients between mean annual rainfall values at six different locations: the single GCM grid cells that contain lakes Challa, Naivasha, Masoko and Malawi, and the two larger grid boxes which delineate the Challa/Naivasha and Masoko/Malawi regions. The lower left half of the figure shows these correlations for the period 1979-2005 in the six GCMs considered in this study (CCSM4, CESM1, GISS-E2-R, IPSL-CM5A-LR, MPI-ESM-P, BCC-CSM1-1; only the first ensemble member r1i1p1 is considered) plus the model mean, and in the average of four gridded observation datasets (GPCC-v6, GPCP-v2.2, CMAP and PREC/L, see references in Section 2.3.1), in the order shown below the main panel. The upper right half of the figure shows the same results for the period 850-1850 AD (*past 1000*). Squares with a central white circle represent combinations for which the null hypothesis of no correlation can be rejected at the 5% level.

the Masoko/Malawi region. The dipole between the eastern coastal ‘Horn of Africa’ region and the interior rift-valley region highlighted in Tierney et al. (2013) is thus not observed at the annual time scale considered here. Although the correlations are quite similar for the recent period and the last millennium, they are somewhat higher in the former. This may be caused by the present-day anthropogenic forcing that induces a coherent response between the selected locations within each model.

Overall, both observations and model results show that the two selected regions are, on the one hand, characterized by different patterns of temporal variability and, on the other hand, representative of the individual grid cells

containing the lake sites, not only regarding annual precipitation changes over the recent period and the last millennium, but also regarding seasonal cycles and annual mean absolute values (not shown).

2.3.3 Mean seasonal cycle and recent trend of the Indian Ocean SSTs

Before checking the ability of the climate models to reproduce the teleconnections between East African rainfall and Indian Ocean SSTs, the current section deals with the estimation of the biases of these models in simulating the observed seasonal cycle and recent trend of the Indian Ocean SSTs. Two different SST datasets are used: version 3 of the Hadley Centre dataset (HadSST3; Kennedy et al., 2011a,b), based on in-situ measurements covering the period from 1850 to 2015 on a $5^\circ \times 5^\circ$ grid, and version 3b of the Extended Reconstructed Sea Surface Temperature dataset (ERSST-v3b; Smith et al., 2008), also based only on in-situ data, which covers the period 1854 to 2015 on a $2^\circ \times 2^\circ$ grid.

Unlike the East African rainfall, GCMs are relatively consistent in their representation of the mean annual cycle of the Indian Ocean SSTs, and agree with recent observations (Fig 2.4). No model is significantly biased, although the amplitude of the simulated cycle is slightly underestimated in the western Indian Ocean (Fig. 2.4-a).

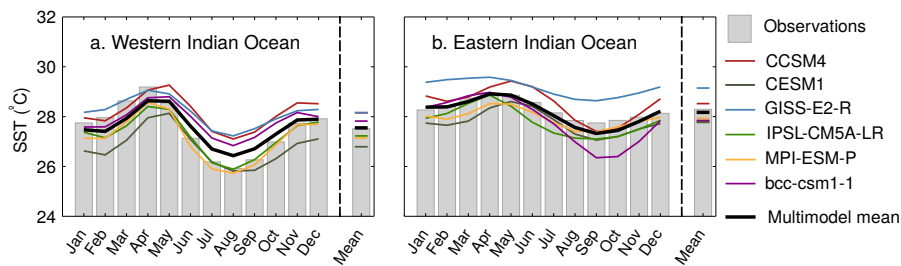


Figure 2.4 – Mean seasonal cycle of SSTs over the western (-8 to 2°N and 40 to 65°E ; a.) and the eastern (-10 to 0°N and 80 to 105°E ; b) Indian Ocean in observations (bar plots, average of the datasets ERSST-v3b (Smith et al., 2008) and HadSST3 (Kennedy et al., 2011a,b)) and in six CMIP5 models (curves) over the period 1900-2005. Only the first ensemble member of each GCM is used (r1i1p1).

The climate models also simulate relatively well the observed recent upward trend of the Indian Ocean SST (Fig. 2.5), with correlation coefficients with observations ranging from 0.69 for MPI-ESM-P to 0.80 for CCSM4, the correlation between the multimodel mean and the observations reaching 0.83.

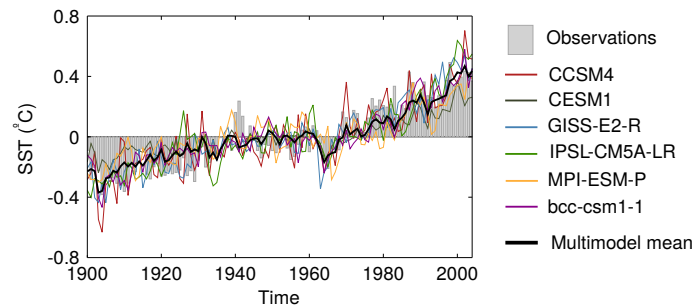


Figure 2.5 – Annual mean anomalies of the Indian Ocean SSTs (bounded by the coordinates -50 to 20°N and 25 to 105°E) in observations (bar plots) and in six CMIP5 models (curves) over the period 1900-2005. Only the first ensemble member of each GCM is used (r1i1p1). The reference period used to compute the anomalies is 1900-2005.

2.3.4 Large-scale tele-connections

In addition to the evaluation of the mean states, it is important to assess the ability of climate models to represent the observed patterns associated with the inter-annual variability of the East African rainfall. Although it is not our goal here to study the mechanisms responsible for the simulated variability, this is illustrated by analyzing the correlations between East African precipitation and tropical SSTs, the latter being indeed considered as a direct driver of precipitation over East Africa (e.g. Goddard and Graham, 1999; Ummenhofer et al., 2009). Since the proxy-based reconstructions used in this study are considered to represent mean annual conditions, interest is here mainly on mean annual results. However, mean annual results for East Africa's hydroclimate represent a combined picture, as the relative amplitudes and the strength and character of tele-connections between the East African rainfall and tropical SSTs at the inter-annual time scale are different from one season to another.

For both regions, the largest correlations between the observed rainfall and SSTs are found during the boreal autumn (OND), with the well-known pattern

of positive (negative) correlation between the East African rainfall and western (eastern) Indian Ocean SSTs, as well as SSTs in the central/eastern (western) equatorial Pacific (Fig. A2 and A4 OND), which resembles the SST pattern during an El Niño phase of ENSO and a positive phase of the IOD. This period corresponds to the short rains season in Challa/Naivasha and to the start of the single rainy season in Masoko/Malawi farther south (Fig. 2.2). For the other seasons, the spatial pattern of correlations differs between the two study areas, with the greatest difference occurring during boreal winter (JFM). In Challa/Naivasha, where rainfall is relatively low during this transition period between the short rains and the long rains, it appears to be positively correlated with SSTs over the central/north Indian Ocean (Fig. A1 JFM). In contrast, just a few isolated significant correlations are found between rainfall in boreal winter over Masoko/Malawi and tropical SSTs (Fig. A3 JFM), although this period marks the annual maximum in precipitation (Fig. 2.2). Tele-connections to tropical SSTs are weak in both regions during the boreal spring (AMJ; Fig. A1 and A3 AMJ), which corresponds to the long rains in Challa/Naivasha and to the end of the rainy season in Masoko/Malawi; and are also weak also during the boreal summer (JAS; Fig. A2 and A4 JAS), which is the principal dry season in both regions (Fig. 2.2).

When considering mean annual results, the correlations between the observed precipitation over the Challa/Naivasha region and SSTs show a pattern similar to that during the short rains, although damped, with positive correlations in the western Indian Ocean and central/eastern tropical Pacific and negative ones centered on Indonesia (Fig. 2.6-a left). In contrast, the correlations between the Masoko/Malawi rainfall and SSTs after computing annual averages are mostly weak and non-significant in the Indian Ocean and negative over the Indonesian region while some zones in the Pacific show positive correlations (Fig. 2.6-b left), even though the correlations pattern for boreal autumn (OND) rainfall is similar to that found using precipitation over Challa/Naivasha. In both cases, the spatial pattern of correlations derived from the different combinations of datasets show very similar results, with spatial correlations of the obtained patterns always exceeding 0.80.

Out of the six GCMs, only CESM1 and MPI-ESM-P seem to simulate relatively well the spatial pattern of correlations between the Challa/Naivasha rainfall and SSTs (Fig. 2.4-a). However, the match with observations is far from perfect as shown by the relatively low correlation coefficients between



Figure 2.6 – Pearson correlation coefficients between the mean annual rainfall over the Challa/Naivasha region (a, upper three rows) or Masoko/Malawi region (b, lower three rows) and global SSTs in observations and climate models (here, only the first member r11p1 is used) for the period 1950-2000. In areas overprinted with white circles, a null hypothesis of no correlation can be rejected at the 5% level. No data are available from grey areas.

simulated and observed rainfall-SST correlation maps, with values equal to 0.27 and 0.16, respectively (Table A2). GISS-E2-R, IPSL-CM5A-LR and BCC-CSM1-1 display totally different patterns compared to observations, and CCSM4 even simulates an opposite pattern, with positive (negative) correla-

tions between the simulated precipitation over the Challa/Naivasha area and the eastern Indian Ocean (central/eastern Pacific).

Model results show a wide range of tele-connections between the Masoko/Malawi rainfall and SSTs (Fig. 2.6-b.). None of them shows the observed pattern of correlations, which is weak but seems robust given that it is similar regardless of the combinations of datasets used. GISS-E2-R, IPSL-CM5A-LR and MPI-ESM-P correlations patterns are positively, although poorly, correlated with the data (Table A2). However, the correlation coefficients obtained by GISS-E2-R and IPSL-CM5-LR are the result of a compensative effect between wrong seasonal tele-connection patterns (Fig. B3 and B4). CCSM4 simulates a strong relationship between Masoko/Malawi and Indian and Pacific Ocean SSTs, but in an opposite sign than expected, with negative correlations in the western Indian Ocean and central/eastern equatorial Pacific, and positive correlations in the eastern Indian Ocean. Although CESM1 can simulate the pattern observed in boreal winter, no correlation is found when considering annual mean results.

Overall, most climate models fail to simulate observed tele-connections of the Challa/Naivasha and Masoko/Malawi rainfall to large-scale SST patterns at the inter-annual scale. Annual smoothing makes these tele-connections complex and of relatively limited magnitude, especially for the Masoko/Malawi rainfall. However, this cannot by itself explain the low model performance since their skill is not greatly improved when only considering the OND rainfall, shown to be strongly and robustly correlated to Indian and Pacific SSTs in observations. Only CESM1, MPI-ESM-P and, to a lesser extent, BCC-CSM1-1 simulate the observed patterns for both regions during this season (Table A2). Inconsistent with the observations, IPSL-CM5A-LR and GISS-E2-R simulate a relatively homogeneous tele-connection pattern throughout the year, while the strong seasonality depicted by CCSM4 has almost everywhere incorrect signs. MPI-ESM-P and CESM1 thus tend to stand out by their positive correlation with annual observations in both regions and only in Challa/Naivasha, respectively, for the right reasons. These mitigated results are, to some extent, consistent with the study of Rowell (2013). Indeed, although using different methodologies and selected areas, this author has shown that the tele-connections between rainfall over central East Africa (roughly corresponding to the Masoko/Malawi region) and both equatorial Pacific and Indian Ocean SSTs are particularly hard for CMIP5 models to re-

produce. Furthermore, Rowell (2013) reached a similar conclusion about the tele-connections between rainfall over the greater Horn of Africa region, which includes the Challa/Naivasha region, and equatorial Pacific SSTs.

2.4 Reconstructed and simulated hydroclimate over the last millennium

2.4.1 Hydroclimate changes deduced from proxy-based reconstructions

Notwithstanding chronological uncertainty, the Challa and Naivasha proxy records display clear differences during the first four centuries of the last millennium. In particular, the former shows a general drying trend while the opposite is recorded in the latter (Fig. 2.7). However, from around 1400 AD the conditions inferred from these two records are similar: both show relatively dry conditions followed by a wetting trend peaking between about 1700 and 1750 AD. After this peak, both hydroclimate reconstructions depict an abrupt transition towards a dry period in the early 19th century, followed by smaller-scale hydroclimate fluctuations at Naivasha and a clear wetting trend at Challa.

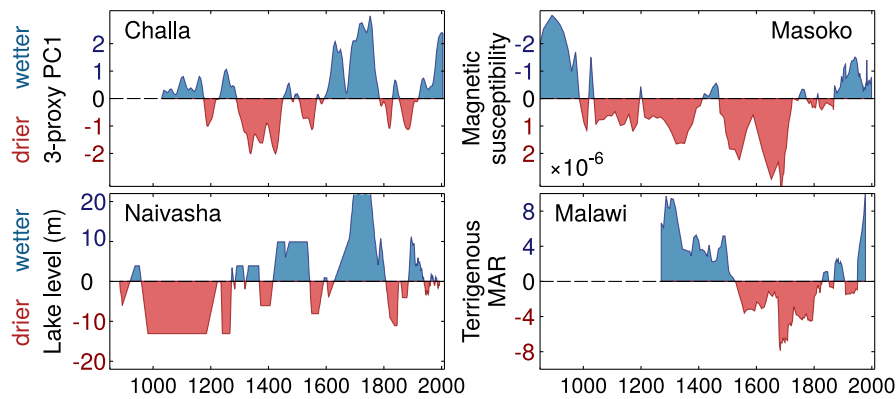


Figure 2.7 – Lake-based moisture-balance reconstructions used in this study; references with details on the proxies are provided in Section 2.2.2. Ordinate axes for each proxy are oriented such that wetter (drier) hydroclimate conditions point upward (downward).

Contrasting with Challa and Naivasha, lakes Masoko and Malawi both show a general drying trend culminating around 1700 AD, before an increase in humidity towards the present. However, (multi-) decadal hydroclimate changes overlying these long-term trends often strongly differ between the two records.

The differences between the Challa and Naivasha reconstructions on the one hand and between the Masoko and Malawi reconstructions on the other can be viewed as a measure of how representative these records are of hydroclimatic variability within each region. Certainly, the differences partly reflect real local features due to different exposure to the principal seasonal moisture sources related to distance to the sea, topography etc. However, a significant fraction of the difference observed within each pair of records is likely due to uncertainty in the reconstructions themselves, due to the compound effects of i) dating uncertainty in these lake-based proxy records, ii) differences in hydrology and local catchment processes influencing a lake's (or in the case of δD , its surrounding vegetation) sensitivity to climate, and/or iii) the fact that the used hydroclimate proxies have a specific and different relationship with temporal variation in our target of reconstruction, i.e. the climatic moisture balance. Importantly, the point here is that the differences between the two pairs of records are larger than those within each pair. Each pair can thus be considered as representative of a distinct hydroclimatic region (cf. Tierney et al., 2013).

2.4.2 Interpretation of proxy-based reconstructions from a model perspective

Lakes are complex hydrological systems. To understand their dynamics, it is necessary to account for the inflow and outflow from rivers and surface runoff, rainfall on the lake surface, evaporation from the lake surface, groundwater inflow and/or outflow, as well as interactions with the aquifer surrounding the lake (e.g. Becht and Harper, 2002). These processes are not represented directly in relatively coarse-resolution GCMs. These models simulate the large-scale moisture balance, i.e. precipitation minus actual evaporation (P-E), the latter depending on potential evaporation and soil moisture content. Each of the sedimentary proxies used in the lake-based climate reconstructions can be qualitatively interpreted as smoothed versions of the local-to-regional climatic

moisture balance, at least when considered on multi-decadal to centennial time scales. P-E is thus the model variable that has been chosen here for comparison with the reconstructed histories of lake-level fluctuation, catchment runoff or drought-season severity, depending on the lake (see Section 2.2.2). This section describes the relative contributions of rainfall and of evaporation in P-E, which allows knowing whether the respective regions containing each record are more influenced by precipitation or evaporation.

It was shown in Section 2.3.1 and in Section 2.3.2 that, despite their relative proximity, the two spatial domains used in this study, Challa/Naivasha and Masoko/Malawi, are quite different in terms of precipitation amount and seasonality as well as in precipitation trends through time. The study of P-E balance confirms that. Indeed, climate models simulate mean P-E values over Challa/Naivasha which are close to zero throughout the last millennium (Fig. 2.8-a). In contrast, all models show positive P-E values for the Masoko/Malawi region during the last millennium (Fig. 2.8-b). The higher P-E for Masoko/Malawi compared to Challa/Naivasha is as expected due to higher precipitation, which more than compensates for higher evaporation and thus leads to larger river runoff.

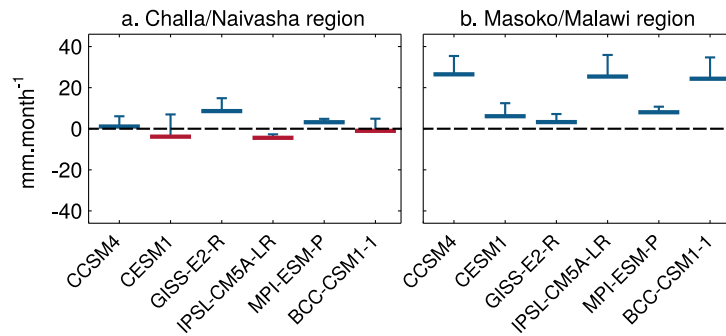


Figure 2.8 – Mean annual precipitation minus mean annual evaporation (horizontal bars), and standard deviation of annual precipitation minus the standard deviation of annual evaporation (vertical bars) using the entire last-millennium results (850–2005) for each GCM. Red (blue) color means that evaporation (precipitation) dominates.

If we consider the standard deviation of variation in P and E through the last millennium, there is a consensus among models that P is more variable from year to year than E, for both regions (vertical bars in Fig. 2.8, which

all plot upwards). This implies that most changes of P-E over time are due to changes in precipitation. Differences between the standard deviation of P and of E are also generally greater in Masoko/Malawi. This can be explained in all models except GISS- E2-R by a weaker relationship between P and E in this region than in Challa/Naivasha, as evidenced by weaker correlation coefficients (Table 2.2). Higher correlations indeed mean that a change in P is more often accompanied by a similar change in E, which tends to bring variances closer.

Table 2.2 – Pearson correlation coefficients between simulated rainfall and simulated evaporation in the Challa/Naivasha and Masoko/Malawi regions over the pre-industrial portion of the last millennium (850-1850 AD).

	Challa/Naivasha	Masoko/Malawi
CCSM4	0.66*	0.09*
CESM1	0.57*	0.35*
GISS-E2-R	0.71*	0.95*
IPSL-CM5A-LR	0.91*	0.69*
MPI-ESM-P	0.68*	0.62*
BCC-CSM1-1	0.88*	0.70*

* significant at the 5% level

These results are robust throughout the last millennium where they remain relatively stable over time, even during the recent past where one could expect evaporation to increase relative to precipitation due to anthropogenic warming (not shown). Moreover, rainfall still has a dominant role in explaining changes in P-E when considering timescales longer than annual, since approximately the same picture is observed when filtering model results using a loess method with a window of 100 years (not shown).

2.4.3 Comparison between reconstructions and model results

As briefly discussed in Section 2.4.2, the link between simulated and reconstructed variables is only indirect, which means that the magnitude of simulated P-E that should best fit the reconstructions is unknown. Consequently, the focus in this comparison is on common relative changes, rather than on their magnitude in absolute values. For better readability of the figures, each time series has been linearly standardized so that the maximum of the absolute values equals 1. A 100-year smoothing is applied to the model results in

order to resemble temporal variability in the reconstructions. Our choice of a 100-year smoothing window is partly subjective, since the resolution of the proxy-based reconstructions varies through time due to a non-linear relationship between sediment depth and age. However, using other window widths for this smoothing does not lead to major changes in the results.

Despite this smoothing, most model curves do not show any distinct long-term trend in the past millennium as observed in the proxy-based reconstructions, and have weaker fluctuations at the centennial scale than the reconstructions (Fig. 2.9). The correlation coefficients between model results and reconstructions, computed annually using interpolations for the reconstructed time series, are presented in Table B3. Most coefficients are low and non-significant at the 0.05% level, and can be for a same site either positive or negative depending on the models, which implies that there is no common signal between models and data but neither among models.

No individual site is characterized by an overall better agreement between model and data since the averages of correlation coefficients for each lake are close to zero. Furthermore, taking the four sites into account, no model appears to match substantially better the reconstructions than another. Nevertheless, some isolated positive correlations should be mentioned: CESM1 shows one positively and statistically significant correlation of 0.43 with the average of the reconstructions from Masoko and Malawi, and GISS-E2-R correlates with the average Challa/Naivasha time series with a coefficient of 0.38.

This general model-data mismatch could arise from several reasons. First, as discussed in Section 2.3.2, the results from climate models are selected from the two regions Challa/Naivasha and Masoko/Malawi, that do not necessarily match the spatial representativity of proxy data, or may have trouble in representing the regional atmospheric dynamics responsible for changes in lake hydrology. Note that if we consider only the individual grid cells which contain the proxy data sites, the correlation coefficients are not substantially affected (not shown). This is consistent with the high correlations found for each model simulation between the individual grid cells and the larger spatial domain which contains them (Fig. 2.3). Second, the variables compared are different. Here, simulated regional P-E is indeed compared to reconstructed lake level, catchment runoff, or seasonal drought severity depending on the site (see Section 2.2.2). P-E, which mostly depends on variation in precipitation (see Section 2.4.2), is certainly related to these reconstructed variables,

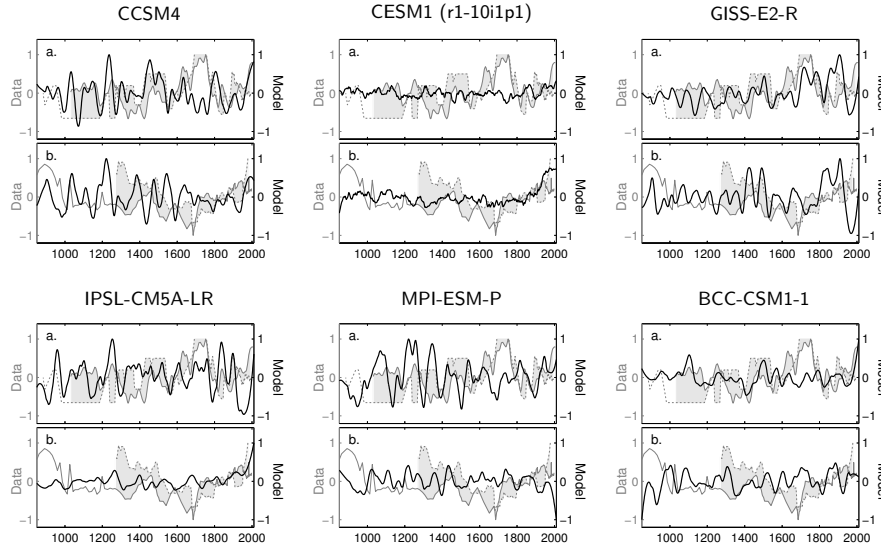


Figure 2.9 – Comparison between last-millennium time series of the reconstructions (in grey) and of P-E simulated by six GCMs (in black) averaged over the Challa/Naivasha region (a), with the Naivasha record shown as dashed line and the Challa record as solid line; and over the Masoko/Malawi region (b), with the Malawi record shown as dashed line and the Masoko record as solid line. In both regions, the area between the between the two records is shaded in light grey. Both proxy-based and simulated time series are presented as anomalies with respect to the whole period, and are linearly standardized so that the absolute maximum equals 1. Ordinate axes are oriented such that wetter (drier) conditions point upwards (downwards). Model time series are annual mean values filtered using a loess method with a window of 100 years. For the CESM1 model, the black curve is the median of the ten ensemble members previously standardized and smoothed.

but sometimes in an indirect way that is difficult to assess precisely. Third, our model results only consider the immediate effect of P-E and do not account for long-term effects of a change in P-E. However, lake level during a particular year strongly depends on lake level during previous years. To address this issue, we applied a first-order autoregressive model (AR-1) to each simulated time series. The AR-1 process is a simple persistence model where a realization of the system depends on the value at one time step earlier. This thus allows emulating a system with a chosen amount of memory. However, although this produces time series with low-frequency changes that are sim-

ilar to the reconstructions, general model-data agreement is not substantially improved (Section A3).

Simulations with different GCMs are driven by similar climate forcings (see Section 2.1), which are thus expected to put a similar imprint on all time series. However, all model results seem different, which raises the question whether external forcing has any impact on the simulated hydroclimate. The lack of common timing among models in the simulated events actually suggests that the hydroclimate fluctuations are mostly or exclusively driven by internal variability.

2.5 The contribution of forced and internal variability in simulated hydroclimate change

2.5.1 Hydroclimate changes over the past millennium

Whether the simulated East African hydroclimate results from internal variability or from changes in forcing is assessed in two steps: first by investigating potentially common signals among models, and second by comparing variability of the last-millennium hydroclimate changes against control simulations. In the previous section we suggested that little or no link can be established between last-millennium hydroclimate changes simulated by the different models. Indeed, if we first consider the Challa/Naivasha region, most correlations between P-E time series simulated by different models are not statistically significant and close to zero (Fig. 2.10). Actually, the fact that there is no positive correlation between hydroclimate curves from different models does not necessarily mean that there is no impact of forcing in each model. Indeed, the effect of changes in forcing may be different from one GCM to another, especially at the still relatively small spatial scale considered in this study.

In this regard, it is of interest to note that for the only model for which multiple ensemble members were available (CESM1), there is also no correlation between the different ensemble members that differ only in slightly different air temperature at the start of the experiments (Otto-Bliesner et al., 2015). This means that the forced response has a much smaller magnitude than internal variability for P-E in that region, even at the multi-decadal time scale.

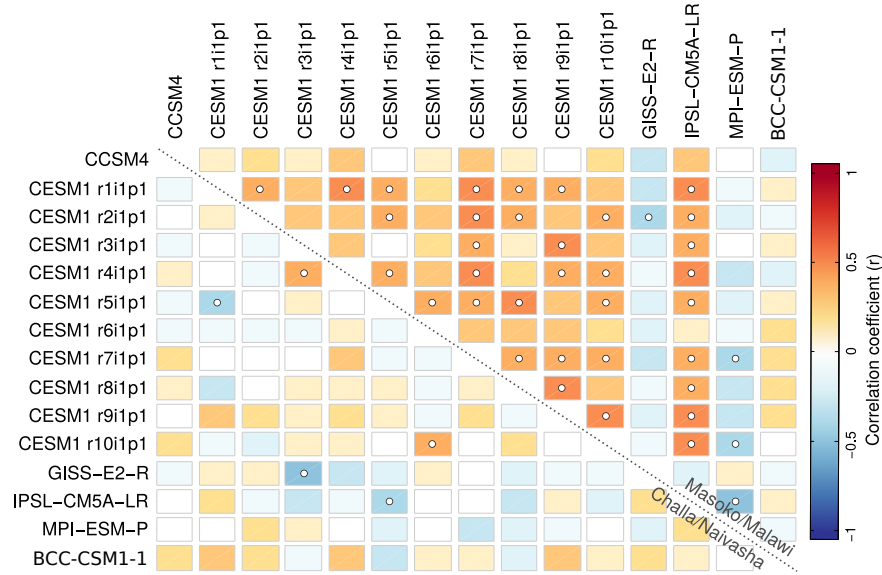


Figure 2.10 – Pearson correlation coefficients between annual mean P-E over the last millennium (850-2005) as simulated by the different GCMs. The results were filtered using a loess method with a window of 100 years. The lower left half of the figure shows the results for the Challa/Naivasha region, the upper right half the results for Masoko/Malawi. Squares with a central white circle represent combinations for which the null hypothesis of no correlation can be rejected at the 5% level.

For the Masoko/Malawi region, the link between the hydroclimate time series produced by different models is also low. However, most ensemble members of CESM1 show significantly positive correlations with each other, mainly due to a common increase in P-E around 1800. This suggests an impact, although limited, of external forcing on the Masoko/Malawi hydroclimate during the last two centuries, as simulated by CESM1. For the other models, if a significant response to forcing is present, it is too different between them to be revealed by the correlation, except for IPSL-CM5A-LR which correlates positively with the ensemble members of CESM1.

To complement this diagnostic, Fig. 2.11 shows P-E time series for the two regions from forced simulations, along with the variability in these time series and in the *pre-industrial control* runs, represented by the ± 2 standard-deviation envelope. It shows that the P-E variance simulated over the last mil-

lennium is in most cases very similar to that of the control simulations. This indicates that the radiative changes from GHGs, solar variability and relatively short-lived volcanic effects have little influence on the selected variables compared to internal variability. The only noticeable difference in these variances is found for Masoko/Malawi in two of the models, CESM1 and IPSL-CM5A-LR, which both show a P-E increase in recent time. The similarity of the variances of P-E in fixed and time-varying forcing experiments, along with the lack of common P-E changes in the last-millennium simulations among models, obviates the possibility of general agreement with the proxy results, and suggests that any apparent proxy-model agreement for this time period and these regions is coincidental. To obtain more information on the processes driving the simulated hydroclimate changes over the last millennium, the next section deals with the stability of tele-connections at different frequencies, and with the impact of changes in forcing on those tele-connections.

2.5.2 The stability of large-scale tele-connections

Since East African hydroclimate fluctuations in models are mostly driven by rainfall (see Section 2.4.2), only rainfall is considered here. The present-day large-scale tele-connections have already been studied in Section 2.3.4. Hence, the period considered in this section is 850-1850 AD, which allows us to focus on the last millennium without the influence of anthropogenic forcing.

Annual mean large-scale tele-connections between the simulated East African rainfall and tropical SSTs over the (pre-industrial portion of the) last millennium differ substantially among models. However, for rainfall over the Challa/Naivasha region, all GCMs except CCSM4 agree in simulating a dipole pattern over the Indian Ocean, with positive (negative) correlations in the western (eastern) half of the basin (Fig. 2.12-a), i.e. consistent with the IOD pattern and its effect on the East African precipitation. Interestingly, while CCSM4, CESM1 and MPI-ESM-P do not show much difference between last-millennium and recent tele-connections, this dipole is not simulated by GISS-E2-R, IPSL-CM5A-LR and BCC-CSM1-1 with recent rainfall data (1950-2000; Fig. 2.6-a). The role of equatorial Pacific SSTs during the last millennium is less clear among models, with both positive and negative correlations depending on the model selected.

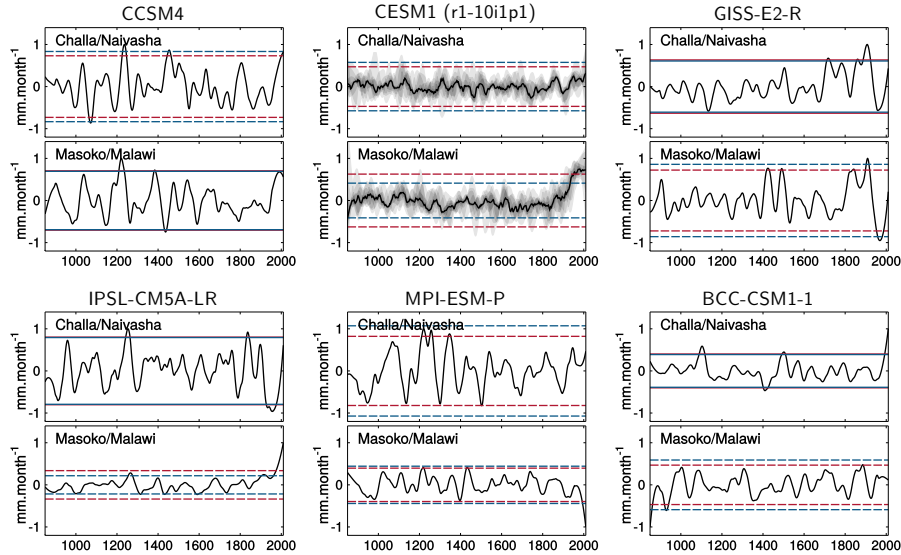


Figure 2.11 – Simulated time series of P-E (black lines) over the Challa/Naivasha and Masoko/Malawi regions throughout the last millennium (850-2005). Results are mean annual values smoothed using a loess filter with a window of 100 years, and are presented as anomalies with respect to the entire period. The horizontal red lines are displayed on both sides of the zero line at two times standard deviation of the smoothed time series. The horizontal blue lines also represent 2 standard deviations on both sides of zero but based on the time series from pre-industrial control simulations. The horizontal lines are dashed if the variance of the simulation with time-varying forcing is significantly different (F-test, considering a 5% level) from the variance of the simulation with fixed forcing; if not, it is solid. For the CESM1 model, the black line is the median of the ten ensemble members, while their range is shown in grey shading.

Patterns of correlations between the simulated Masoko/Malawi rainfall and SSTs are more heterogeneous (Fig 2.12-b). CCSM4 and MPI-ESM-P show a comparable picture as with Challa/Naivasha rainfall, which is also the case for CESM1 but only for the Indian Ocean. GISS-E2-R and, to a lesser extent, IPSL-CM5A-LR show an opposite pattern, and BCC-CSM1-1 suggests almost no link between Masoko/Malawi rainfall and SSTs. For this region, the pre-industrial last-millennium tele-connections differ strongly from the recent ones in all models except CCSM4 and GISS-E2-R (Fig. 2.6-b). For this pre-industrial last-millennium period, the effect of changes in forcing on inter-

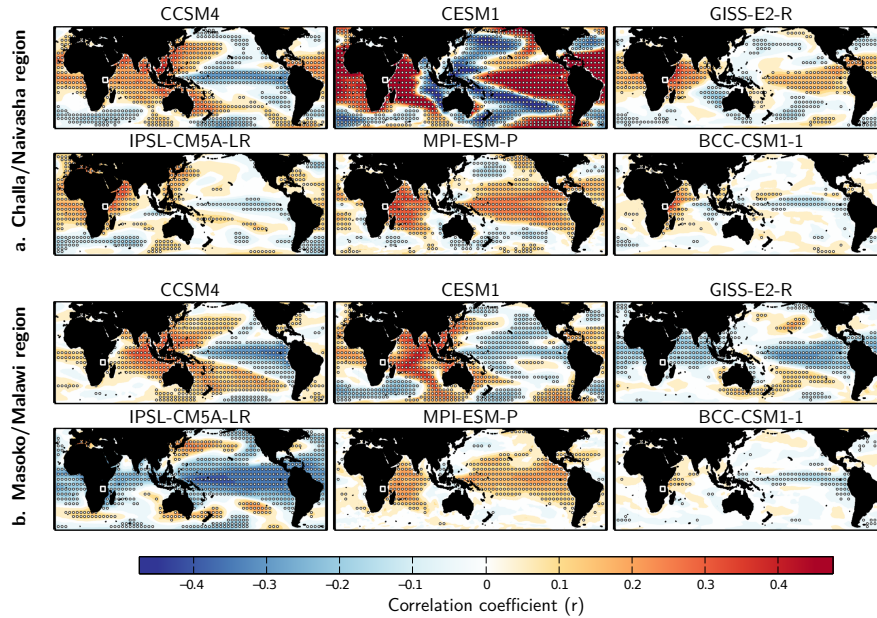


Figure 2.12 – Pearson correlation coefficients between global SSTs and the mean annual rainfall over the Challa/Naivasha (a) and Masoko/Malawi (b) regions, in climate models for the period 850-1850 AD. In areas overprinted by white circles the null hypothesis of no correlation can be rejected at the 5% level.

annual rainfall tele-connections appears to be weak, given the very similar results of the last millennium runs (Fig. 2.12) and of the *pre-industrial control* runs for both regions (Fig. B5). It is thus likely that the difference in tele-connection patterns between the pre-industrial period and recent decades, observed in the models GISS-E2-R, IPSL-CM5A-LR and BCC-CSM1-1, is due to anthropogenic forcing. Based on the control runs of two global climate models, Tierney et al. (2013) showed that at longer than decadal time scales, rainfall over the Horn of Africa region (including our Challa/Naivasha domain) is mostly influenced by Indian Ocean SSTs. This is investigated here using smoothed GCM-simulation results with a window of 100 years. Such a smoothing decreases drastically the number of degrees of freedom resulting in only a few statistically significant patterns of correlation in control simulations (Fig. 2.13). As regards the simulated Challa/Naivasha rainfall, the correlation with SSTs displays the characteristic Indian Ocean dipole in all models except

CCSM4. The dipole is especially clear and robust in CESM1, the model that best matches observations regarding recent large-scale tele-connections (Section 2.3.4). By contrast, at this centennial time scale, the link between the Masoko/Malawi rainfall and the Indian Ocean is neither consistent among models nor robust in these control simulations. Additionally, for neither Challa/Naivasha nor Masoko/Malawi a significant link is obtained with Pacific SSTs.

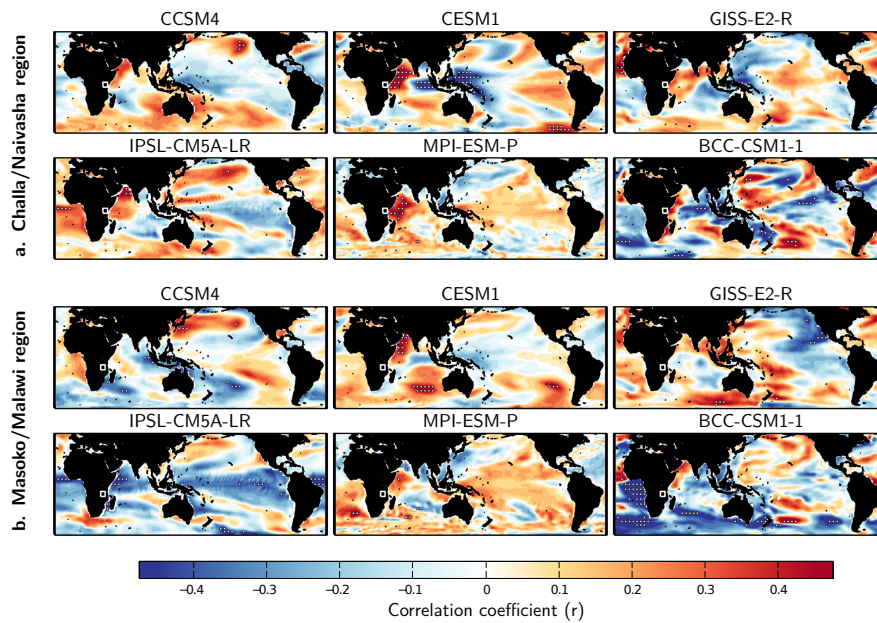


Figure 2.13 – Pearson correlation coefficients between global SSTs and the mean annual rainfall over the Challa/Naivasha (a) and Masoko/Malawi (b) regions, using the *pre-industrial control runs* of the climate models. Rainfall and SSTs are mean annual values smoothed using a loess filter with a window of 100 years. In areas overprinted by white circles the null hypothesis of no correlation can be rejected at the 5% level.

The patterns of correlations become completely different when considering the smoothed last millennium simulations with changes in forcing (Fig. 2.14). Most correlations are not significant and relatively weak. Interestingly, in the forced runs no Indian Ocean dipole is observed in most model results at this centennial time scale and, more generally, there is substantial difference in

modeled large-scale tele-connections between simulations with time-varying forcing (Fig. 2.14) or fixed forcing (Fig. 2.13). This suggests that, at the centennial time scale, the forcing is able to mask the weak correlations associated with natural variability throughout the pre-industrial portion of the last millennium (850-1850 AD). Nevertheless, the response of the different models to the same forcing strongly varies. Some models are characterized by a very homogeneous pattern of correlation that can be both negative or positive, while some models show a more patchy pattern.

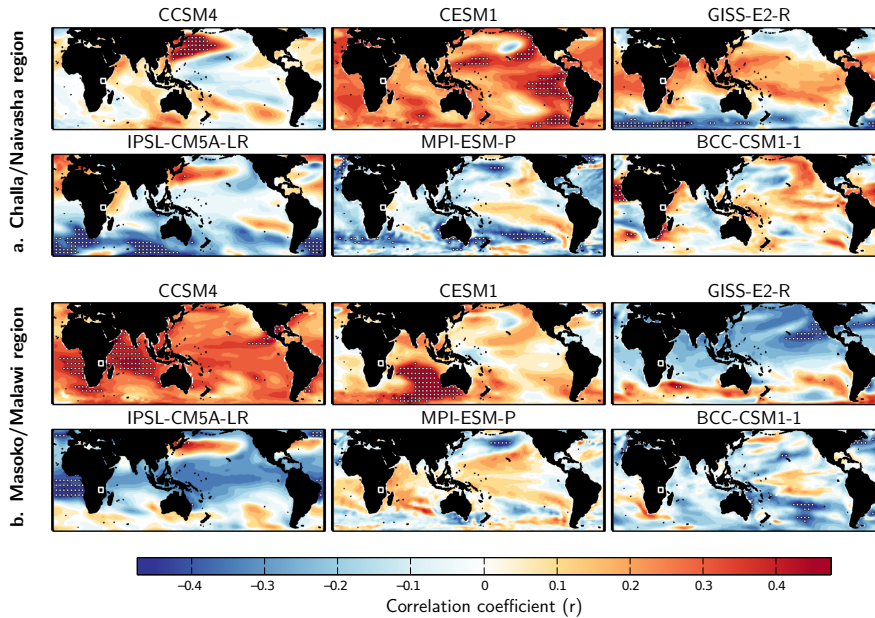


Figure 2.14 – Pearson correlation coefficients between global SSTs and the mean annual rainfall over the Challa/Naivasha (a) and Masoko/Malawi (b) regions in climate models for the pre-industrial period 850-1850 AD. Rainfall and SSTs are mean annual values smoothed using a loess filter with a window of 100 years. In areas overprinted by white circles the null hypothesis of no correlation can be rejected at the 5% level.

2.6 General discussion and conclusions

Our analysis of East Africa’s hydroclimate over the last millennium is based on recent observational data, lake-based proxy reconstructions and the results of

six GCMs. When compared to recent observations (1979-2005), simulations of all models represent the unimodal seasonality of precipitation characterizing the Masoko/Malawi spatial domain rather well. The bimodal seasonality characterizing the Challa/Naivasha domain is generally less well captured by the GCMs, with a systematic underestimation of the long rains and overestimation of the short rains. Model skill in simulating present-day (i.e., observed) large-scale tele-connections between East African precipitation and tropical SSTs strongly varies among the GCMs, with MPI-ESM-P and CESM1 generally displaying the most consistent patterns.

Both model results and observations show that lakes Challa and Naivasha, on the one hand, and Masoko and Malawi, on the other hand, are located in hydroclimatically relatively homogeneous regions. However, these two regions display a different rainfall seasonality and different large-scale tele-connections with ocean SSTs. Furthermore, the lake-based proxy reconstructions from these two regions even show opposite moisture-balance changes during the second half of the last millennium, highlighting the strong spatial heterogeneity characterizing the East African hydroclimate dynamics. Comparing the simulated variable P-E with the available hydroclimate reconstructions, we found the contribution of rainfall to be dominant relative to actual evaporation in both regions. Model results and reconstructions show a very different timing of hydroclimate fluctuations over the past millennium. Furthermore, there is no common signal among the time series modeled by different GCMs. This suggests that the simulated P-E in East Africa is largely driven by internal variability rather than by common forcing, at least until 1850 AD. After that, half of the GCMs used simulate a relatively clear, but model-specific, response to forcing. These results are in line with those of Coats et al. (2015) who showed, using approximately the same set of GCMs, that multi-decadal droughts in the North American Southwest over the last millennium do not seem to be driven by external forcing. Similar conclusions were also reached by Kelley et al. (2012) who used GCMs to investigate the possibility that the late winter drying trend observed in the Mediterranean region could be explained by anthropogenic forcing. In contrast, Fallah and Cubasch (2015) suggested an impact of forcing on multi-decadal droughts in Asia over the last millennium, namely through alteration of atmosphere-ocean interactions. These contrasting results could mean that some regions are more sensitive to forcing than others.

At the inter-annual time scale, models show robust tele-connections between mean annual Indian Ocean SSTs and rainfall over the Challa/Naivasha region during the pre-industrial portion of the last millennium, with positive (negative) correlation in the western (eastern) half of the basin. The link between rainfall over the Masoko/Malawi region and SSTs is less clear among models. At this time scale, the effect of external forcing on large-scale tele-connections appears negligible. Although most of times not significant, the Indian Ocean dipole is still present using time series smoothed to highlight centennial variations, but only in fixed-forcing simulations. When taking into account the last millennium forcing, the result is completely different, with relatively homogeneous patterns of correlation between precipitation in both regions and tropical SSTs. This means that, although the correlation pattern between the Challa/Naivasha rainfall and Indian Ocean SSTs remains relatively similar for both inter-annual and centennial time scales when only natural variability is present, it is overwhelmed by the effect of forcing at the centennial time scale. An interesting question is whether the forcing actually alters the dynamical link between the East African rainfall and SSTs, or if it only masks it because of a different impact on continental rainfall and SSTs. Answering this question is out of the scope of this study, but it is of interest for the interpretation of records used for reconstructing phenomena like the IOD. Indeed, if dynamical relationships are not stable when considering different time scales, a record calibrated in observations of the recent period may not be representative of the studied phenomena over longer time scales.

Analyzing an ensemble of models was particularly useful here to test the robustness of the results. Additionally, using individual models that contain several ensemble members allows attributing the simulated change to internal variability or to forcing, which is crucial in the present context of climate change in the vulnerable East African region. On the other hand, using multi-model mean results to study variation in local hydroclimate during the last millennium should be avoided. It does not make sense to average hydroclimate time series which are mostly driven by internal variability, since this would only result in concealing already weak responses.

CHAPTER

RECONSTRUCTING EAST AFRICAN RAINFALL AND INDIAN OCEAN SEA SURFACE TEMPERATURES OVER THE LAST CENTURIES USING DATA ASSIMILATION

This chapter is based on the following submitted article:

Klein, F. and Goosse, H. (2016). Reconstructing East African rainfall and Indian Ocean sea surface temperatures over the last centuries using data assimilation. *Submitted to Climate Dynamics*.

Abstract

The relationship between the East African rainfall and Indian Ocean sea-surface temperatures (SSTs) is well established. The potential interest of this covariance to improve reconstructions of both variables

over the last centuries is examined here. This is achieved through an off-line method of data assimilation based on a particle filter, using hydroclimate-related records at four East African sites (Lake Naivasha, Lake Challa, Lake Malawi and Lake Masoko) and SSTs-related records at six oceanic sites spread over the Indian Ocean to constrain the Last Millennium Ensemble of simulations performed by CESM1. Skillful reconstructions of the Indian SSTs and East African rainfall can be obtained based on the assimilation of only one of these variables, when assimilating pseudo-proxy data deduced from the model CESM1. The skill of these reconstructions increases with the number of particles selected in the particle filter, although the improvement becomes modest beyond 99 particles. When considering a more realistic framework, the skill of the reconstructions is strongly deteriorated because of the model biases and the uncertainties of the real proxy-based reconstructions. However, it is still possible to obtain a skillful reconstruction of the whole Indian Ocean SSTs based only on the assimilation of the six SST-related proxy records selected, as far as a local calibration is applied at all individual sites. This underlines once more the critical role of an adequate integration of the signal inferred from proxy records into the climate models for reconstructions based on data assimilation.

3.1 Introduction

EQUATORIAL Eastern Africa is characterized by a heterogeneous spatial distribution of precipitation due to local and regional meteorological features, which are influenced by the presence of numerous lakes and a complex topography. Consequently, this region supports a large variety of environments, ranging from deserts with rainfall less than 200 mm per year to tropical rain forests with annual rainfall above 2000 mm (Nicholson, 1996). Due to the seasonal migration of the Intertropical Convergence Zone (ITCZ) back and forth across the equator, the annual cycle of rainfall is bimodal over much of East Africa, with a first and main rainy season occurring from March to May (the so-called long rains) and a second from October to December (short rains). Nonetheless, this seasonal distribution of precipitation can change rapidly over short distances and some regions, such as the Ethiopian and the Eastern Highlands, only have one rainy season with a peak during boreal and austral summer, respectively (e.g. Owiti and Zhu, 2012; Yang et al., 2015).

Because of the influence of large-scale atmospheric and oceanic factors, the temporal variability of rainfall tends to be more homogeneous than the mean patterns over the region (Nicholson, 2014). At the inter-annual scale, numerous observation-based (e.g. Ogallo et al., 1988; Hastenrath et al., 1993; Saji et al., 1999; Webster et al., 1999; Nicholson and Selato, 2000; Clark et al., 2003; Schreck and Semazzi, 2004; Izumo et al., 2014) and model-based (e.g. Goddard and Graham, 1999; Ummenhofer et al., 2009; Rowell, 2013; Klein et al., 2016; Schubert et al., 2016) studies have emphasised the teleconnections between the short rains, which are the main driver of the inter-annual variability of the East African rainfall (e.g. Nicholson, 1996, 2014), and the Indian and Pacific SSTs. Specifically, precipitation over East Africa during the short rains correlates positively with the SSTs over the Western Indian Ocean and the Central and Eastern Pacific Ocean, while the correlations are negative over the Eastern Indian Ocean. This link appears robust and has been reported using various techniques including correlation coefficients (Ogallo et al., 1988; Goddard and Graham, 1999; Saji et al., 1999; Clark et al., 2003; Rowell, 2013; Klein et al., 2016; Schubert et al., 2016), visual comparison of different 2D fields (Webster et al., 1999; Ummenhofer et al., 2009), empirical orthogonal functions (Schreck and Semazzi, 2004; Goddard and Graham, 1999; Saji et al.,

1999) and composite (Saji et al., 1999) or harmonic (Nicholson and Selato, 2000) analyses. However, such statistical methods do not allow for the identification of the physical nature of this link. For instance, they do not provide insight as to whether the SSTs are responsible for the East African rainfall variability, or whether both variables react to a common forcing.

The goal of this study is to perform reconstructions of the East African rainfall and Indian Ocean SSTs over the last millennium, based on the covariance observed between those two variables, through a data assimilation method. The covariance can indeed be used to potentially obtain better reconstructions of the two variables considered, and can be particularly useful over periods when instrumental observations are lacking and indirect proxy records are scarce. In contrast to more classical statistical methods, data assimilation has the advantage not to rely on the length of a calibration period and on the quality of the records during this period, which could be a problem in Africa. Furthermore, it can handle a potential non-stationarity of the covariance, related for instance to changes in the mean state, and ensure that the reconstruction for both variables is compatible with the physics of the system as represented by the model. Although a link between the East African rainfall and SSTs in the Pacific has also been reported, it seems less robust than the one in the Indian Ocean (Klein et al., 2016), and will thus not be considered in the present study.

Since the early 1990s, data assimilation has been extensively employed in various Earth science disciplines including meteorology, oceanography and hydrology (e.g. Park and Xu, 2009; Dee et al., 2011; Balmaseda et al., 2015). In palaeoclimatology, it is still considered as an emerging topic (e.g. Matsikaris et al., 2015), despite growing interest over the past 15 years (e.g. von Storch et al., 2000; Goosse et al., 2006; Cresspin et al., 2009; Widmann et al., 2010; Hakim et al., 2016). When applied to palaeoclimatology, data assimilation aims to combine information from model results and proxy-based reconstructions to find estimates of past climate changes. Here, a particle filter method has been preferred over other data assimilation methods such as forcing singular vectors (e.g. Barkmeijer et al., 2003) or pattern nudging (e.g. von Storch et al., 2000). This ensemble filter method has the advantage to respect the model physics by selecting a set of climate in agreement with observation within the range of a finite ensemble, taking into account the uncertainties. While this choice may potentially limit the skill of the reconstructions given

that the real climate has a large state space with many degrees of freedom, the method has already led to very satisfying results in conditions similar to the ones of the problem studied here (e.g. Goosse et al., 2012; Mairesse et al., 2013). Furthermore, ensemble particle filters are relatively easy to implement and do not require any information about the model. If a satisfactory reconstruction can be obtained where the constraint is applied, the empirical information will then be propagated to various climate variables and spatially spread, based on the physics and the dynamics of the climate model used.

In the last decade, two types of ensemble-based methods of data assimilation have been applied to study the past millennium climate (e.g. Matsikaris et al., 2015). First, data assimilation can be used to update an ensemble of simulations at regular interval (on-line data assimilation). In this case, the ensemble is generated sequentially, each period depending on the diagnostic made by the data assimilation process on the previous ones. Second, data assimilation can occur a posteriori, making use of an existing ensemble of simulations (off-line data assimilation). The on-line method have advantages compared to the off-line one. Indeed, it maintains the temporal consistency. Furthermore, it is expected to bring better results than an off-line method as the slow component of the climate system, such as the oceans, can propagate an information forward in time (Matsikaris et al., 2015). However, if the predictability of the variables of interest is limited between two assimilation steps because of a dominant role of the chaotic nature of the system, an on-line technique would not outperform an off-line one.

The main interest of an off-line method lies in the fact that we can use existing ensemble of simulations, saving a significant amount of computational time. This allows applying a data assimilation scheme in higher resolution general circulation models (GCMs) and considering larger ensembles, such as in Bhend et al. (2012) or in Steiger et al. (2014). In contrast, on-line data assimilation methods are usually used in palaeoclimatology with simplified models with a relatively coarse resolution such as in Cresspin et al. (2009), Goosse et al. (2012), or in Klein et al. (2013), or with relatively small ensembles (Matsikaris et al., 2015). We do not expect a large predictability of the East African rainfall on the interannual time-scale, meaning that the additional information brought by an online method would be limited, as shown in previous works (e.g. Annan and Hargreaves, 2012). Furthermore, an off-line procedure is also much more flexible as many tests can be performed on a single existing ensemble,

while new simulations are required each time in the on-line approach. Hence, an off-line method is preferred over an on-line one in the present study, using the ensemble of ten simulations recently performed (Otto-Bliesner et al., 2015) with the Community Earth System Model version 1.1 (CESM1; Hurrell et al., 2013), which is the largest ensemble to date made with a GCM that covers the last millennium. Moreover, CESM1 is adequate here since its correlations pattern between the East African rainfall and large-scale SSTs over the recent past is the closest to observations, compared to five other GCMs (Klein et al., 2016).

To our knowledge, reconstructing simultaneously precipitation and SSTs over long periods using data assimilation has never been attempted before. Hence, in order to test the methodology and to identify the most critical issues, this study contains several steps gradually increasing in complexity. The most simple case is the assimilation of pseudo-proxies where the data used to constrain model results are derived from the climate model CESM1 itself. The locations of the sites selected for the assimilation are the ones for which actual proxy-based reconstructions are available. In this framework, the model physics is supposed to be perfect as both the pseudo-observations and the model ensemble originate from the same source. Furthermore, the reconstruction target and the uncertainty of the records are perfectly known, the latter being given by the noise imposed on model results to obtain the pseudo-proxies. This setup is thus ideal to assess precisely the performance of the data assimilation method itself. Two sensitivity analyses are performed using this framework, one assessing the effect of the size of the ensemble, and the other looking at the individual effect of each site on the quality of the reconstructions. In a second step, pseudo-proxy data derived from other climate models as well as from recent observations are considered. This allows studying how sensitive the reconstructions are to biases in the model physics. Lastly, real proxy-based reconstructions are used to constraint the model simulations. The selected hydroclimate-related reconstructions describe the water-balance history during roughly the last millennium of Lake Challa, Lake Naivasha, Lake Masoko and Lake Malawi, and are part of the East African hydroclimate synthesis achieved by Tierney et al. (2013). The six SST-related records are derived from the $\delta^{18}\text{O}$ content of coral archives spread over the Indian Ocean, the choice of the records being based on the compilation of Tierney et al. (2015).

This study is structured as follows. The next section describes the climate model used (Section 3.2.1), the data assimilation method (Section 3.2.2), and the different data assimilated, ie. the pseudo-proxies (Section 3.2.3) and the proxy-based reconstructions (Section 3.2.4). Section 3.3 describes the reconstructions of the East African precipitation and Indian Ocean SSTs based on the assimilation of the pseudo-proxy data, Section 3.4 is focussed on the reconstructions performed by assimilating the proxy-based reconstructions. Finally, Section 3.5 presents the discussion and conclusions.

3.2 Methodology

3.2.1 Model results

Data assimilation is based on the ensemble of simulations performed over the period 850–2005 AD with CESM1 (the CESM1 Last Millennium Ensemble or CESM-LME; Otto-Bliesner et al., 2015). This model has an horizontal resolution of about two degrees for the atmosphere and land components, and of about one degree for the ocean and sea-ice components. The CESM-LME represents the largest ensemble to date performed with a GCM covering the last millennium. The ensemble contains ten simulations, which only differ from slightly different air temperatures at the start of the experiments. They are driven through the last millennium by changes in both natural and anthropogenic climate forcings. The solar irradiance variations follow the reconstruction of Vieira et al. (2011), with the spectral variations and ‘11-year’ solar cycle from Schmidt et al. (2012). Changes in the forcing related to volcanic aerosols are derived from Gao et al. (2008). The evolution of the major greenhouse gases (CO_2 , CH_4 and N_2O) is based for the preindustrial period (850–1850 AD) on Flückiger et al. (2002) and MacFarling Meure et al. (2006), and for the recent period on Hansen and Sato (2004). Anthropogenic changes in land use/land cover are first derived from the reconstruction of Pongratz et al. (2009) until 1850, and follow Hurtt et al. (2011) thereafter. Finally, Earth’s orbital parameters are updated every year based on Berger et al. (1993).

3.2.2 Data assimilation method

The off-line ensemble-based method of data assimilation applied here use a particle filter (e.g. van Leeuwen, 2009), as described in Dubinkina et al. (2011). This method has the advantage to be very general. It does not rely on hypotheses such as the Gaussian distribution of the error, as is the case for other ensemble-based methods such as the Kalman filter (van Leeuwen, 2009), and it enables the experiments to be performed off-line, which is needed here. The frequency of the data assimilation is annual, meaning that annual mean values from every members of the ensemble of simulations, called particles, are compared to data each year of the reconstruction period. Based on this comparison, the likelihood of every particles is computed, taking into account the uncertainties of the data. The likelihood is a measure of the ability of the different ensemble members to simulate the signal showed in the data. Depending on the likelihood values, a weight is then attributed to the particles. When the weights of each ensemble member are known for a given year, a weighted mean is computed, which provides the reconstructions for that year.

Only the first nine simulations of the CESM-LME are used in the data assimilation process, because pseudo-proxy data are, in some experiments, derived from the tenth one. When mentioning the CESM-LME later in the text, it thus refers to the first nine members of the ensemble only. An ensemble of nine particles may be too small to obtain a good reconstruction since the range of possible climate states covered by those simulations may not be large enough to reproduce the signal present in the data assimilated (e.g. Goosse et al., 2006). However, it is not possible to perform additional simulations with CESM1 over this period. Hence, in order to increase the size of the ensemble and thus the probability to find a good match between model results and observations for a given year, other years, that will thus differ from the one in observations, are also selected for the ensemble. This is only valid if the forcings play a marginal role compared to natural variability, as appears to be the case for interannual changes in East African precipitation and, to a lesser extent, in Indian Ocean SSTs (Klein et al., 2016). There is thus a priori no reason why the timing of events in observations and in a simulation should be similar, meaning that any model year can be included in the ensemble. For the CESM-LME, this means that the potential size of the ensemble can rise up to 9×1156 members. Here, six ensemble sizes are considered contain-

ing 9, 27, 99, 207, 1035 and 2079 particles. In the first case, the data for a given year are only compared to the nine ensemble member results available for this actual year. When 27 particles are selected, the model results of one year out of 500 are added to the ensemble, besides the nine results of the actual year of the process. To increase the size of the ensemble to 99, 207, 1035 and 2079, one year out of 100, 50, 10 and 5 are considered, besides the actual year of the experiments. Note that we keep using only the first nine ensemble members of the CESM-LME even when real proxy records or results of other models are assimilated, in order to have a meaningful comparison between all experiments.

3.2.3 Pseudo-proxy data

This study starts with the assimilation of the results of the tenth ensemble member of the CESM-LME over the last millennium, at the same locations than the real proxy-based reconstructions that are described in the next section. The cells of the atmospheric and oceanic grids containing the records sites are shown in Fig. 3.1. The variables measured or reconstructed from the proxy data, ie. $\delta^{18}\text{O}$ for the oceanic ones and different hydroclimate-related variables for the East African lakes, are not explicitly simulated by the climate model. Coral $\delta^{18}\text{O}$ changes are directly linked to variations in SSTs (e.g. Juillet-Leclerc and Schmidt, 2001; Stevenson et al., 2013), and East African hydroclimate changes are mostly dependent on precipitation rather than on evaporation in models (Klein et al., 2016). Thus, in a first step, the variable assimilated at the locations of the six oceanic records is yearly averaged SST, while it is yearly averaged precipitation at the locations of the four continental grid cells containing the East African hydroclimate records. The pseudo-proxy time series are generated by the addition to the results of the tenth ensemble member of the CESM-LME of a white Gaussian noise with a standard deviation of 5 mm.month^{-1} for rainfall results and of 0.25°C for SST results, these values corresponding to the data error estimates applied in the data assimilation process. Note that changing these estimates by 20% positively or negatively does not affect significantly the results.

In order to estimate the uncertainty associated to the model biases, the second step of this study consists in assimilating pseudo-proxy data, but taken from other GCMs, ie. MPI-ESM-P (Stevens et al., 2013) and GISS-E2-R

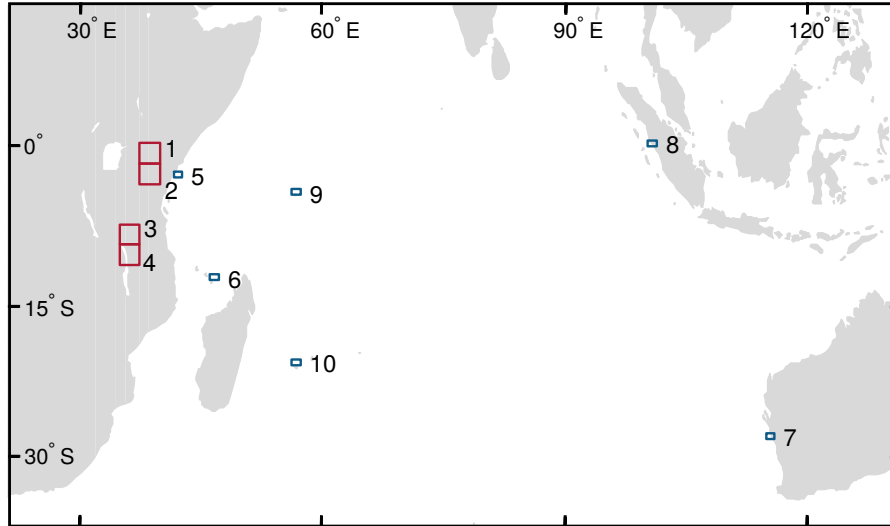


Figure 3.1 – Grid cells of CESM1 containing the sites of the proxy-based reconstructions selected for data assimilation. The red cells belong to the atmospheric grid while blue ones to the oceanic grid. The numbers correspond to the identifier of the reconstructions as shown in Table 3.1.

(Schmidt et al., 2014), as well as from instrumental observations, using the gridded precipitation data set GPCC-v7 (version 7 of the Global Precipitation Climatology Centre data set; Schneider et al., 2014) and the SSTs data set ERSST-v4 (version 4 of the Extended Reconstructed Sea Surface Temperature data set; Smith et al., 2008). The model MPI-ESM-P displays a strong teleconnection between the East African rainfall and Indian SSTs, that is relatively similar than the one simulated by CESM1, while GISS-E2-R shows very weak link between both variables (Klein et al., 2016). These two models are thus good candidates to assess the effect of uncertainties in model physics and dynamics on the quality of the reconstructions. For instrumental observations, the data assimilation process is applied only over the period 1901-2005. The same noise as above is added to the model time series to obtain pseudo-proxies. These different models and gridded data sets do not have the same spatial resolution than CESM1. All results are thus interpolated into the CESM1 continental and oceanic grids before the data assimilation.

3.2.4 Proxy-based reconstructions

The last, and most complex, step of this study consists in assimilating real proxy-based reconstructions of East African hydroclimate and Indian Ocean coral $\delta^{18}\text{O}$. The selection of the hydroclimate reconstructions is based on the compilation achieved in Tierney et al. (2013), which contains seven lake-based East African proxy records covering the last millennium with a time resolution of at least 50 years. As in Klein et al. (2016), the reconstructions originating from Lake Challa, Lake Naivasha, Lake Masoko and Lake Malawi have been selected here. The records from Lake Tanganyika and Lake Edward are discarded because they are located far from the Indian Ocean, which has thus potentially less influence on local hydroclimate. The reconstruction from Lake Victoria is also not included because the representation of this lake is different from one model to another. Indeed, CESM1 and GISS-E2-R simply ignore it, while it is present in the model MPI-ESM-P as a single grid point lake, meaning that the specific conditions imposed by the presence of the lake cannot be reproduced in the simulations.

The hydroclimate reconstructions are based on different proxies, but the four of them can be qualitatively seen as smoothed versions of the local moisture-balance of the areas in which they originate. For Lake Challa, the hydroclimate variation is derived in Tierney et al. (2013) from the first principal component of composite variation in three moisture-balance proxies, that accounts for 40% of the variance in the data (supplementary material of Tierney et al. (2013)). The three proxies are a presumed indicator of catchment runoff (the branched and isoprenoidal tetraether index (BIT); Verschuren et al., 2009), an isotopic proxy for rainfall source and intensity (δD in the leaf waxes of terrestrial plants; Tierney et al., 2011), and a proxy for variation in dry-season length and windiness (varve thickness; Wolff et al., 2011). Regarding Lake Naivasha, the time series is a lake-level reconstruction derived from the sediment lithostratigraphy (Verschuren, 2001), supported by salinity reconstructions based on fossil diatom and midge assemblages (Verschuren et al., 2000). In Lake Masoko, the hydroclimate reconstruction is inferred from the low-field magnetic susceptibility of the sediment, which is a proxy for lake-level changes and/or wind stress. Two such records are available for this lake, one that goes back to -43,300 AD (Garcin et al., 2006) and one that starts around 1500 AD (Garcin et al., 2007). The Masoko time series chosen here

is obtained from Tierney et al. (2013), who used the last millennium of the longer record but with age-depth tie-points translated from the shorter one (Anchukaitis and Tierney, 2013). The hydroclimate reconstruction in Lake Malawi is based on the mass accumulation rate of the terrigenous sediment fraction, suggested to be a runoff proxy (Brown and Johnson, 2005; Johnson and McCave, 2008).

The Indian Ocean coral $\delta^{18}\text{O}$ time series selected in this study are taken from the work of Tierney et al. (2015) who compiled 57 marine coral-based archives in order to reconstruct SST in the tropics over the past four centuries. Out of these 57 records, 13 belong to the Indian Ocean domain, including 12 oxygen isotopic composition of coral carbonate. However, six of them are discarded because located on land in the grid of the CESM model. Thus six time series of coral $\delta^{18}\text{O}$ remain available for our analysis. They originate from Malindi (Cole, 2000), Mayotte (Zinke et al., 2008, 2009), Houtman Abrolhos (Kuhnert et al., 1999), Mentawai (Abram et al., 2008), Seychelles (Charles, 1997) and La Réunion (Pfeiffer et al., 2004). The exact geographic coordinates of those reconstructions, as well as the period they cover, are given in Table 3.1. Note that the comparison of model results and proxy-based reconstructions during the process of data assimilation is made at the model grid cell scale, which means that the spatial representativeness of the data is assumed to match the area of the grid cells in which they are located, shown in Fig. 3.1.

Data assimilation involves an objective comparison between model results and the data assimilated, meaning that both have to represent the same physical quantity. Since the variables reconstructed from proxy records are not included as such in the climate models, a processing is applied to the simulated variables in order to emulate coral $\delta^{18}\text{O}$ and East African hydroclimate. This may potentially affect the quality of the reconstructions. Hence, before assimilating the real proxy-based reconstructions, the impact of assimilating the measured variables, ie. coral $\delta^{18}\text{O}$ and East African hydroclimate, instead of SSTs and precipitation, is investigated. This is done by considering once more the results of the tenth ensemble member of the CESM-LME as the “reality”.

For each ensemble member of the CESM-LME, the model coral $\delta^{18}\text{O}$ is computed based on the linear function of SST and sea surface salinity (SSS)

Table 3.1 – Geographic coordinates and period covered by the proxy time series used in this study.

Id	Location	Lat	Long	Period	Reference
Hydroclimate proxy-based reconstructions					
1	Naivasha	-0.77	36.35	884–1993	Verschuren et al. (2000)
2	Challa	-3.32	37.7	1031–2005	Time series computed in Tierney et al. (2013) based on Verschuren et al. (2009), Tierney et al. (2011) and Wolff et al. (2011)
3	Masoko	-9.33	33.76	452–1999	Time series computed in Anchukaitis and Tierney (2013) based on Garcin et al. (2006, 2007)
4	Malawi	-10	34.22	1270–1978	Brown and Johnson (2005); Johnson and McCave (2008)
Coral $\delta^{18}\text{O}$					
5	Malindi	-3.20	40.10	1887–2002	Cole (2000)
6	Mayotte	-12.65	45.10	1865–1994	Zinke et al. (2008, 2009)
7	Houtman Abrolhos	-28.47	113.77	1794–1994	Kuhnert et al. (1999)
8	Mentawai	-0.13	98.52	1858–1998	Abram et al. (2008)
9	Seychelles	-4.62	55	1846–1995	Charles (1997)
10	La réunion	-21.03	55.25	1832–1995	Pfeiffer et al. (2004)

derived by Thompson et al. (2011):

$$\delta^{18}\text{O}_{\text{CESM1-LME}^{1-10}} = -0.22 \times \text{SST}_{\text{CESM1-LME}^{1-10}} + 0.16 \times \text{SSS}_{\text{CESM1-LME}^{1-10}} \quad (3.1)$$

where SST is expressed in °C and SSS in PSU. The error chosen to obtain the pseudo-proxies is 0.05‰.

It is not possible to apply the same approach for the four hydroclimate proxy-based reconstructions because of the complex and not well understood relationship between those proxies and the East African hydroclimate-related variables, including lake level, catchment runoff or seasonal drought severity depending on the site. In this final test, the model variable that is compared to the data is annually averaged precipitation minus evaporation (P-E). The data assimilation process is performed annually. However, to qualitatively match the temporal resolution of the proxy-based reconstructions, the values considered each year are smoothed by performing averages over sub-periods of ten years. Furthermore, since the reconstructions only provide common relative changes in moisture balance, both the data assimilated (pseudo-proxy data or real-world proxy-based reconstructions) and the model simulations time se-

ries are standardized before the comparison by subtracting their mean over the whole period and by dividing by their standard deviation. The data error taken into account is here estimated to be 0.5, whatever the data considered for the assimilation.

3.3 Reconstructions using pseudo-proxy data

3.3.1 Pseudo-proxies derived from CESM1

In this section, we focus on the experiments performed in the idealized setup, with the assimilation of the tenth ensemble member of the CESM1-LME using the first nine ensemble members as model ensemble.

3.3.1.1 Influence of the number of particles used

As expected, rainfall and SSTs after data assimilation get closer to the pseudo-proxy at the grid points where data are available. For instance, Fig. 3.2-a shows that the root-mean-square error (RMSE) computed from the results in the four grid cells where rainfall is assimilated is much lower with assimilation (red line) than the ensemble mean of the CESM1-LME (black cross), with a decrease of at least 46%. Note that the RMSE is even larger for individual simulations of the CESM-LME than for the ensemble mean (not shown), as classically observed in model-data comparison studies (e.g. Goosse et al., 2005; PAGES 2k-PMIP3 group, 2015). Similarly, the assimilation of SST results improves the representation of SSTs, at least locally (blue line to be compared to the black cross in Fig. 3.2-b), with a decrease in RMSE of 32% in the experiment considering only nine ensemble members. Increasing the number of particles from 9 to 27 and 99 leads to a significant reduction of the RMSE for precipitation and SST. In both cases, using 99 particles allows reaching an RMSE similar to the errors of the pseudo-proxy equals to 5 mm.month^{-1} for rainfall and 0.25°C for SST (horizontal dashed line in Fig. 3.2). Further increasing the number of particles beyond 99 does not lead to significantly better results.

The decrease in RMSE is much weaker on precipitation when assimilating SSTs, and conversely. With an ensemble of nine simulations, the assimilation of SSTs improves only very slightly the representation of rainfall over the

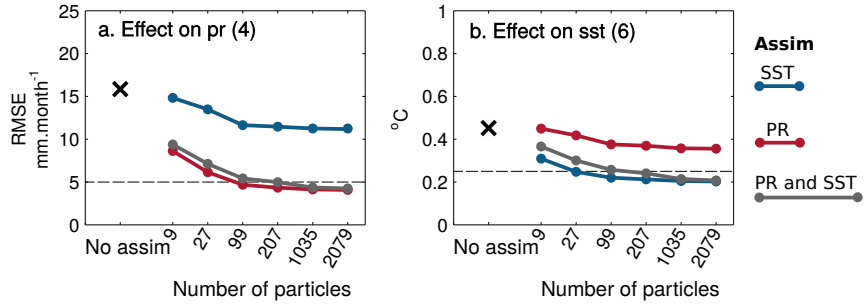


Figure 3.2 – RMSE between rainfall (a) and SSTs (b) from the tenth ensemble member of the CESM-LME (pseudo-proxy assimilated) and the CESM-LME without data assimilation (black cross, ensemble mean) and with data assimilation considering different number of particles (dots, weighted mean of the ensemble). The experiments assimilating only the four East African rainfall results are shown in blue, the experiments that only consider the assimilation of the six Indian SST results are shown in red, and the experiments with the assimilation of both variables in grey. The horizontal black lines represent the data error.

four East African grid cells considered, while the representation of SSTs at the six oceanic grid cells is not impacted by the assimilation of East African rainfall. However, when taking into account a larger ensemble, data assimilation of one variable (rainfall or SSTs) has an increasingly important effect, although modest, on the other variable, at least until 99 particles. For the precipitation, the decrease in RMSE due to the assimilation of SSTs compared to the ensemble mean reaches 15% and 27% with ensemble sizes of 27 and 99, respectively. Similarly, assimilating precipitation improves the representation of SSTs with a decrease in RMSE compared to the ensemble mean of 8% and 17% in the experiments considering 27 and 99 model simulations. As before, the improvement of the results when further increasing the ensemble size beyond 99 particles is virtually nil. When assimilating both East African rainfall and Indian Ocean SSTs (gray line in Fig. 3.2), the decrease in RMSE observed on the East African rainfall is very similar than when assimilating only the rainfall. In contrast, a larger ensemble of more than 207 model simulations is needed to have an adequate representation of the SSTs and to reach similar results than when assimilating the SSTs only.

It is interesting to estimate whether the improvement shown in Fig. 3.2 propagates over the whole Indian Ocean and eastern equatorial region of

Africa, or whether it is restricted to the grid cells considered for the assimilation. Hereafter, the diagnostic used to measure the skill of the reconstructions based on data assimilation is the coefficient of efficiency (CE). Compared to the RMSE, this allows removing the influence of the variance of the time series on the diagnostic, and thus a more meaningful comparison of the quality of the reconstruction at different grid cells. The CE was first proposed by Nash and Sutcliffe (1970) for hydrological model assessment, and is classically used to measure the skill of any reconstruction, in particular when using data assimilation (e.g. Steiger et al., 2014). It is defined for a time series including n samples as:

$$CE = 1 - \frac{\sum_{i=1}^n (x_i - \hat{x}_i)^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad (3.2)$$

where x is the “true” time series, $\bar{x}$ is the “true” time series mean, and $\hat{x}$ is the reconstructed time series, ie. the output after data assimilation. CE ranges from one, corresponding to a perfect fit between the “true” and the reconstructed time series, to $-\infty$. It is negative when the mean of the “true” time series is a better estimate than the reconstructed time series, meaning that the latter has no skill.

Fig. 3.3 shows the CE for all the grid cells of our study area, computed from rainfall and SST results, for three types of experiments performed (assimilation of rainfall, of SST and of both variables). It first confirms that nine particles are not sufficient to obtain a skillful reconstruction of the “true” spatial patterns (six top panels in Fig. 3.3). In this case, the reconstruction skill is restricted to the variable that is actually assimilated, and the improvement is not propagated far away from the location where the constraint is applied (crosses on the figure). In areas where no data is assimilated, the CE are often negative, meaning that the reconstruction is worse than a climatological mean. There are no more negative CE when increasing the number of particles to 2079 (six bottom panels in Fig. 3.3). In this case, the assimilation of rainfall (first column in Fig. 3.3) provides a good reconstruction of rainfall as well as of SSTs over the western and the eastern equatorial Indian Ocean. Assimilating SSTs (second column in Fig. 3.3) leads to an improved representation of SSTs and of rainfall all over the Indian Ocean, although the consistency between the pseudo-observations and our reconstruction is weaker for precipitation in the central Indian Ocean. It also leads to a skillful reconstruction of rainfall in East

Africa, over the south of the Horn of Africa and east of Lake Victoria. In contrast, values of CE are close to zero further south, including at the locations of the lakes Masoko and Malawi. The reconstruction obtained when assimilating both variables basically combines the positive effects of both single-variable assimilation experiments (third column in Fig. 3.3).

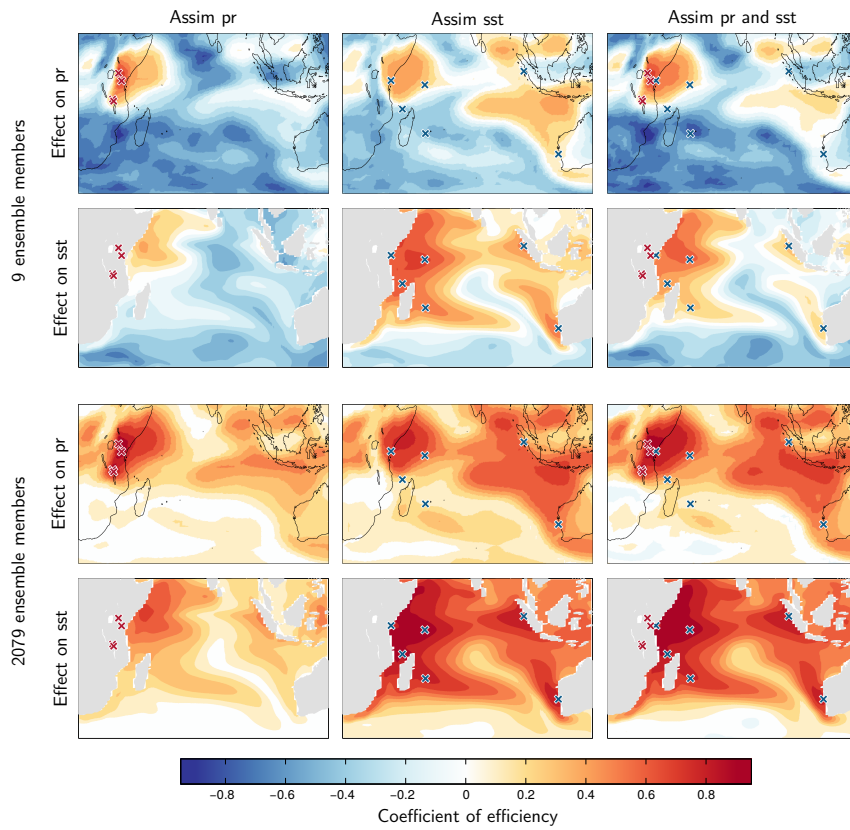


Figure 3.3 – Coefficients of efficiency in the reconstructions based on the CESM-LME with data assimilation of the tenth ensemble member of the CESM-LME over the whole last millennium period (850–2005 AD). For each experiment (assimilation of the four rainfall results only (left), assimilation of the six SST results only (middle), and assimilation of both (right)), the coefficients of efficiency for annual mean rainfall and SSTs are shown. The six top panels show the results using 9 particles while the six panels below show the results with 2079 particles. The crosses indicate the locations where data are assimilated, and are red in case of rainfall and blue in case of SST.

Since the best reconstructions are achieved using 2079 particles, and since the computational cost of these experiments is relatively modest thanks to the use of an off-line data assimilation method, this ensemble size will be used in all the following experiments shown in this study.

3.3.1.2 How time-consistent is the data-assimilated model output?

Fig. 3.2 and 3.3 show that a sufficient number of particles is needed to obtain skillful reconstructions. Besides the model results for the actual year considered, results of other years must thus also be included to have a large ensemble and increase the range of available climate states. However, the drawback is that the time may be disrupted in the reconstruction. In this section, we analyze if the filter preferentially select the model year corresponding to data or if the time consistency has only a weak influence.

Fig. 3.4 shows the years of the particles selected in the reconstructions for each year of experiment, grouped by periods of ten years for a better readability. In the case of the assimilation of rainfall alone (Fig. 3.4-a), the particles chosen for each year are distributed very homogeneously over the whole last millennium. Every year appears thus interchangeable, which means that no period is characterized by a substantial modification of annual precipitation throughout the last millennium compared to others. In particular, the impact of volcanic eruptions, whose the ten most important are represented by red bars with a length proportional to the quantity of sulphate aerosols released, is not visible.

The picture is different when the Indian Ocean SSTs are assimilated (Fig. 3.4-b). In this case, the particles selected by the filter come more often from corresponding years of simulation than from other years, as depicted by the dark diagonal line. Moreover, the impact of volcanic activity is visible. When a volcanic eruption is observed, the probability to select a particle characterized by a high aerosol load is higher, although it does not necessarily correspond to the same period in the observation. Indeed, for the particle filter, the different eruptions are interchangeable, meaning that their effect on Indian SSTs are relatively similar, and goes beyond the natural variability of SSTs over the last millennium. Finally, in the case of the assimilation of both rainfall and SSTs, the situation becomes very noisy, the forced variability of the SSTs appearing masked by the natural variability of the East African rainfall (Fig. 3.4-c).

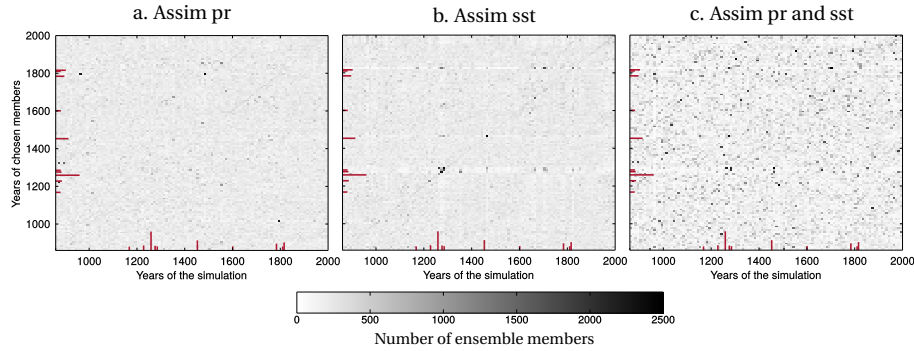


Figure 3.4 – Years of the particles selected in the data-assimilated model output versus reconstructed years, for data assimilation constrained by precipitation (a), SSTs (b) and both (c), using 2079 particles. The years are grouped by periods of ten years for a better readability. The red bars are the ten largest volcanic eruptions of the last millennium, with length proportional to the amount of sulphate aerosol released, based on Gao et al. (2008).

Overall, the reconstructions are thus characterized by a strong time inconsistency, although to a lesser extent in the reconstruction with data assimilation of SSTs.

3.3.1.3 Sensitivity analysis to the pseudo-proxy data assimilated

Some of the pseudo-proxies have more influence on the skill of the reconstructions at the large-scale than others. To investigate the contribution of individual records, we have performed data assimilation experiments constrained by each pseudo-proxy time series separately, using 2079 particles. The assimilation of rainfall over Naivasha and over Challa (id 1 and 2 in Fig. 3.1) yields very similar results (Fig. 3.5). It allows obtaining a virtually perfect match between the simulation with data assimilation and the pseudo-proxy assimilated over those two grid cells. In contrast, the reconstruction has only little or even no skill farther south, in the grid cells containing the lakes Masoko and Malawi (id 3 and 4 in Fig. 3.1). This situation is valid the other way around, when assimilating precipitation in Masoko and Malawi. This emphasizes the strong heterogeneous nature of the East African hydroclimate, as already shown in previous studies (e.g. Tierney et al., 2013; Klein et al., 2016). Assimilating rainfall over Challa and Naivasha improves the representation of Indian SSTs

over the six grid cells considered, the best skill being obtained over the Seychelles (id 9 in Fig. 3.1) while the worse one, but still with a positive CE, in the location which is the farthest away from East Africa, ie. in the Houtman Abrolhos, located west of Australia (id 7). In contrast, rainfall over Masoko and Malawi brings nearly no skill to reconstruct Indian Ocean SSTs, as shown by the CE close to zero in every oceanic grid cells.

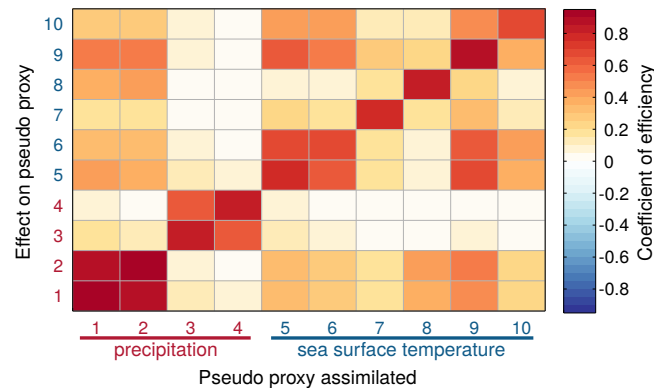


Figure 3.5 – Coefficient of efficiency at the ten grid cells considered in this study (see locations in Fig. 3.1), for each sensitivity experiment in which only one pseudo data is assimilated, using 2079 particles.

The skill brought by the assimilation of individual SST records appears more homogeneous than when considering the East African rainfall: the representation of SSTs over all oceanic grid cells and of rainfall over Challa and Naivasha grid cells is improved in every sensitivity experiments, as depicted by the positive CE. In contrast, there is no experiment with data assimilation of SST that provides skillful reconstruction of rainfall over Masoko and Malawi. Despite these similarities, some differences are also visible among the six experiments. The Houtman Abrolhos and Mentawai sites (id 7 and 8) seem to be the most isolated. Indeed, the values of the CE of the reconstructions achieved by assimilation of these results at the other sites are the lowest, and the improvements lead by the assimilation of the results of the other sites is weaker there than elsewhere. This can be easily explained by the fact that Houtman Abrolhos and Mentawai are located very far from the other records (id 7 and 8 in Fig. 3.1). On the contrary, out of the six oceanic sites considered, the

Seychelles is characterized by the largest impact on the reconstruction skill, which can be explained by its central localization within the Indian Ocean.

In summary, the SSTs reconstructions performed by the assimilation of rainfall in Challa and in Naivasha are skillful in all the oceanic sites considered, although the quality of the reconstructions decreases with the distance. Symmetrically, rainfall over Challa and Naivasha are improved when assimilating Indian Ocean SSTs. In contrast, rainfall over Masoko and Malawi appears to be isolated from the rainfall farther north but also from the Indian Ocean SSTs.

3.3.2 Pseudo-proxies derived from other GCMs and recent observational data

This section focuses on the assimilation of time series derived from the GCMs MPI-ESM-P and GISS-E2-R, and from instrumental observations over the 20th century, which is an intermediary step before assimilating the real proxy-based reconstructions throughout the last millennium. The physics of MPI-ESM-P, GISS-E2-R and of the reality being different than the one in CESM1, the ensemble of particles may not be able to adequately reproduce the covariance present in the data. The resulting reconstructions are thus expected to be less skillful than when assimilating the tenth ensemble member of the CESM-LME. Only the reconstructions using 2079 particles, ie. the best ones (Fig. B1, B2 and B3), are shown. A study of the time distribution of the particles selected for each year of reconstruction has been done for these experiments. The results are roughly similar to the ones obtained with the assimilation of the tenth ensemble member of the CESM-LME (Fig. 3.4), although the effect of forcings is more marked here in the simulations with data assimilation of SSTs. These results are available in the supplementary material in Section B.2.

Despite the similarities in the teleconnections between the East African rainfall and Indian SSTs simulated by MPI-ESM-P and CESM1 (Klein et al., 2016), the reconstruction based on the assimilation of MPI-ESM-P has a lower performance than when assimilating the tenth ensemble member of the CESM-LME (Fig. 3.6). The assimilation of precipitation alone leads only to a very local improvement in the representation of the East African rainfall. The skill of the reconstruction rapidly decreases away from the data locations, to reach values of CE close to zero in most of the regions displayed in Fig. 3.6, or even

negative, for instance in the south of the Horn of Africa. Furthermore, the assimilation of precipitation has virtually no positive effect on Indian SSTs. In contrast, assimilating SSTs over the six grid cells considered allows having a good reconstruction of the SSTs over all the Indian Ocean, but does not improve the representation of rainfall with often negative CE values. Finally, assimilating both the East African rainfall and SSTs basically leads to the addition of the effects of the single-variable assimilations.

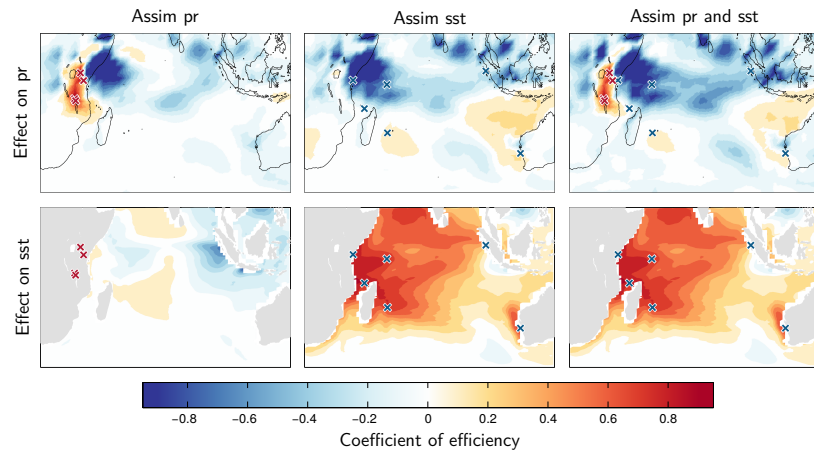


Figure 3.6 – Coefficients of efficiency in the reconstructions based on the CESM-LME with data assimilation of pseudo-proxies derived from the last millennium simulation performed by MPI-ESM-P over the whole last millennium period (850–2005 AD), using 2079 particles. For each experiment (assimilation of the four rainfall results only (left), assimilation of the six SST results only (middle), and assimilation of both (right)), the coefficients of efficiency for annual mean rainfall and SSTs are shown. The crosses indicate the locations where data are assimilated, and are red in case of rainfall and blue in case of SST.

The situation is relatively similar when considering the simulation with data assimilation of the results from the model GISS-E2-R (Fig. 3.7), characterized by a very weak relationship between the East African rainfall and Indian SSTs (Klein et al., 2016). Using the SSTs from six grid cells only as a constraint for the assimilation is sufficient to have a good reconstruction of SSTs over the whole Indian Ocean, but this does not lead to any improvement in the representation of rainfall, some regions being even characterized by reconstructions worse than a climatological mean. Once again, the assimilation

of East African rainfall does not lead to a propagation of the information away from the locations where the constraint is applied. There is, however, a difference with the results of the model MPI-ESM-P. When assimilating pseudo-proxies of both rainfall and SSTs derived from GISS-E2-R, the quality of the SST reconstruction decreases compared to the case in which only SST is assimilated. This illustrates the inconsistency of the representation of the link between rainfall and SSTs in the models CESM1 and GISS-E2-R.

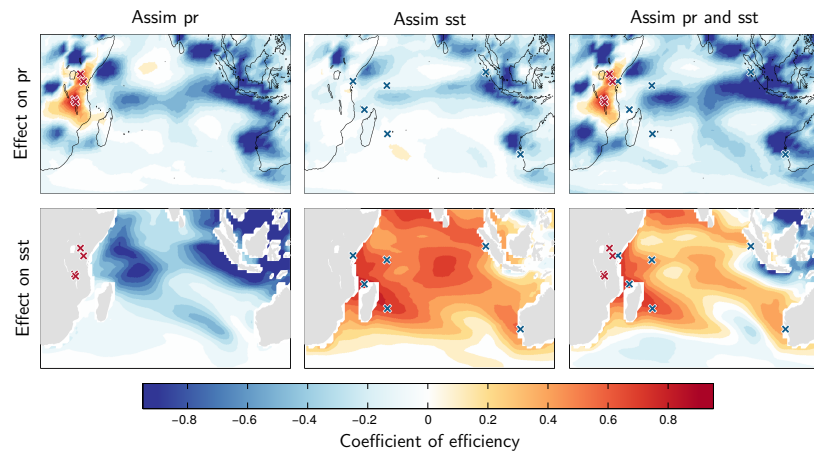


Figure 3.7 – Coefficients of efficiency in the reconstructions based on the CESM-LME with data assimilation of pseudo-proxies derived from the last millennium simulation performed by GISS-E2-R over the whole last millennium period (850–2005 AD), using 2079 particles. For each experiment (assimilation of the four rainfall results only (left), assimilation of the six SST results only (middle), and assimilation of both (right)), the coefficients of efficiency for annual mean rainfall and SSTs are shown. The crosses indicate the locations where data are assimilated, and are red in case of rainfall and blue in case of SST.

GPCC-v7, the data set selected for rainfall, only covers the land-surface. This prevents any assessment of the reconstruction skill of precipitation over the Indian Ocean. Nevertheless, we can see in Fig. 3.8 that the results obtained when assimilating instrumental observations over the last century are very similar to those when assimilating GISS-E2-R time series. Indeed, only taking into account the four rainfall results does not improve the representation of precipitation elsewhere than where the constraint is applied, while, in contrast, the six assimilated time series of SSTs appear to be enough to re-

construct SSTs over the whole the Indian Ocean. However, the quality of this reconstruction is substantially decreased when also assimilating rainfall time series.

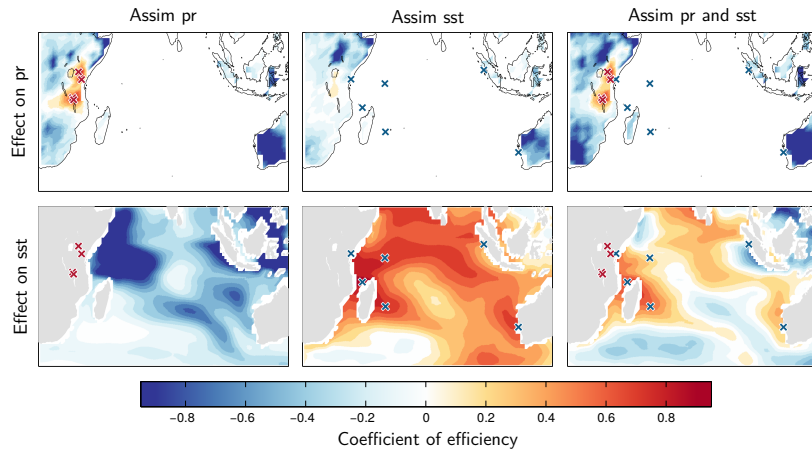


Figure 3.8 – Coefficients of efficiency in the reconstructions based on the CESM-LME with data assimilation of the time series derived from the data sets ERSST-v4 (for SSTs) and GPCC-v7 (for rainfall) over the period 1900-2005 AD, using 2079 particles. For each experiment (assimilation of the four rainfall results only (left), assimilation of the six SST results only (middle), and assimilation of both (right)), the coefficients of efficiency for annual mean rainfall and SSTs are shown. The crosses indicate the locations where data are assimilated, and are red in case of rainfall and blue in case of SST. The data set of rainfall only covers the land-surface.

Compared to the perfect model experiments, assimilating rainfall time series from other sources than CESM1 no longer provides valuable reconstructions of rainfall and of SSTs over the Indian Ocean. In fact, the reconstructions are often worse than a climatological mean, characterizing contradictions in the physics and the dynamics represented in the different data sets. Furthermore, assimilating both rainfall and SST tends to worsen the reconstructions obtained when assimilating the SSTs alone, illustrating the inconsistent covariances of rainfall and SSTs compared to CESM1. In contrast, it is still possible to obtain a skillful reconstruction of the Indian SSTs, based on six time series only.

3.4 Reconstructions using real proxy-based reconstructions

Before using available proxy-based reconstructions over the last millennium, the next section investigates the impact of assimilating the reconstructed variables as defined in Section 3.2.4, ie. the East African hydroclimate and Indian Ocean coral $\delta^{18}\text{O}$, instead of rainfall and SSTs, respectively.

3.4.1 From the simulated towards the reconstructed variables

In order to focus on the loss in reconstruction skill due only to the assimilation of different variables, the results from the tenth ensemble member of the CESM-LME are used for the generation of the pseudo-proxy data, such as in Section 3.3.1. Decadal mean precipitation minus evaporation is the model version of what is reconstructed from hydroclimate-related records. Assimilating this variable instead of annual mean precipitation does not allow obtaining skillful reconstructions of annual rainfall or SST (not shown), which is not surprising giving the strong interannual variability of East African rainfall that is smoothed at the decadal time scale. However, the resulting decadal reconstructions of rainfall and of Indian Ocean SSTs have some skill (Fig. 3.9-a and b), with spatial pattern of CE similar to the ones found in the annual reconstructions achieved with the assimilation of annual mean rainfall. Nevertheless, the skill is somewhat diminished, with a mean CE (averaged over the region shown in Fig. 3.9) of 0.12 instead of 0.19 for rainfall, and of 0.11 instead of 0.19 for SSTs (Fig 3.9-a and b to be compared to Fig. 3.3). The assimilation of annual mean coral $\delta^{18}\text{O}$ instead of annual mean SST does not lead to any substantial decline in the reconstruction skill, the mean CE even being unchanged with values of 0.30 and of 0.48 for pr and of SST, respectively (Fig. 3.9-c and d).

As expected given the previous results, there is a loss of skill in the annual reconstructions of rainfall when assimilating together coral $\delta^{18}\text{O}$ and hydroclimate instead of SST and precipitation, with a mean CE of 0.21 (Fig. 3.9-e) instead of 0.27. This is due to the lack of information on annual rainfall brought by the assimilation of hydroclimate variables. Actually, also considering hydroclimate in addition to coral $\delta^{18}\text{O}$ for the assimilation tends to decrease uniformly the CE of the reconstruction of rainfall compared to the ones obtained with the assimilation of coral $\delta^{18}\text{O}$ alone. By contrast, the skill of the recon-

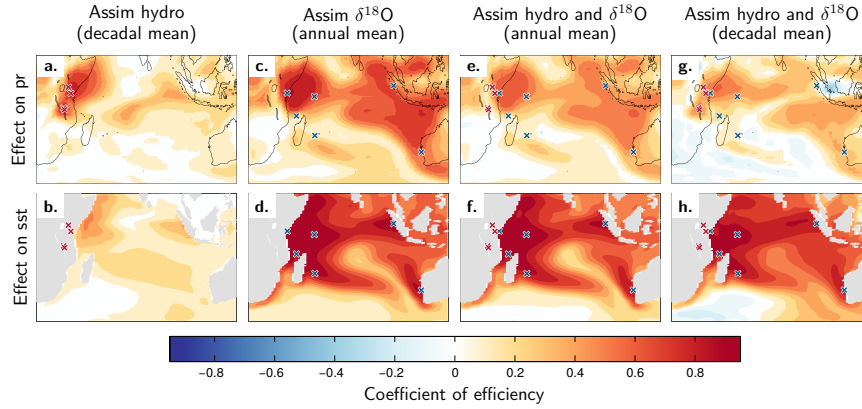


Figure 3.9 – Coefficients of efficiency in the reconstructions based on the CESM-LME with data assimilation of pseudo-proxies derived from the tenth ensemble member of the CESM-LME over the whole last millennium period (850–2005 AD), using 2079 particles. From the left to the right, the panels show the coefficients of efficiency based on rainfall and SSTs from the experiments with data assimilation of the four hydroclimate results only, of the six coral $\delta^{18}\text{O}$ results only, and of both for the last two columns. The temporal frequency on which the coefficients of efficiency are computed is shown in brackets. The crosses indicate the locations where data are assimilated, and are red in case of hydroclimate and blue in case of coral $\delta^{18}\text{O}$.

struction of annual SST is very similar when also assimilating hydroclimate variables together with coral $\delta^{18}\text{O}$ (Fig. 3.9-f), which was also the case when assimilating both annual rainfall and annual SST instead of annual SST alone. Finally, assimilating model-versions of both reconstructed variables also allows having a good reconstruction of decadal mean SSTs (Fig. 3.9-h), with a mean CE of 0.24, and a relatively good reconstruction of decadal mean rainfall (Fig. 3.9-g), with a mean CE of 0.12. In the latter reconstructions, however, the CE over the East African lakes are not as high as in the experiment with data assimilation of hydroclimate only (Fig. 3.9-a).

Overall, no loss of skill in reconstructing rainfall and SSTs is observed when assimilating coral $\delta^{18}\text{O}$ instead of SST. There is a difference in the reconstructions of annual rainfall and SSTs when assimilating hydroclimate instead of rainfall, but which lies on the difference in the time resolution of the records.

3.4.2 Assimilation of proxy-based reconstructions

In this section, we first check if the reconstruction based on data assimilation is in agreement with the data that is assimilated in order to identify potential incompatibilities between the proxy records and model results, before looking at spatial reconstructions. We only consider the experiments with the assimilation of hydroclimate and coral $\delta^{18}\text{O}$ separately, given the negative impact on the reconstructions brought by the assimilation of the combination of those two variables. The large-scale skill of the reconstructions of rainfall and SSTs is assessed hereafter from the difference to recent observational data sets. As before, we show the reconstructions using 2079 particles.

Despite discrepancies between Naivasha and Challa hydroclimate proxy-based reconstructions over the first four centuries of the last millennium, both time series agree from 1400 AD onward on relatively dry conditions followed by a wetting trend peaking between about 1700 and 1750 AD (blue curves in Fig. 3.10-1 and 2). This wet period is followed in both hydroclimate reconstructions by a short dry period before some smaller scale fluctuations. The hydroclimate time series inferred from the Masoko and Malawi records are also characterized by some similar long term changes over the last millennium, but that differ from the Naivasha/Challa pattern (blue curves in Fig. 3.10-3 and 4). Indeed, they agree on a drying trend until about 1700, that is followed by a gradual increase in humidity towards the present time.

Except during the last two centuries at Masoko and Malawi where the model mean shows a trend towards a wetter climate that is consistent with the reconstructed signal, there is no common signal between the proxy-based reconstructed and the simulated hydroclimate without data assimilation. With data assimilation, however, the model time series get much closer to the four reconstructions (green curves to be compared to blue curves in Fig. 3.10), leading to a significative reduction of the RMSE (Table 3.2).

Out of the six coral $\delta^{18}\text{O}$ proxy-based reconstructions, only the one from Houtman Abrolhos goes back to the early 1800s. It shows that this period was characterized by high values of coral $\delta^{18}\text{O}$ relative to the last two centuries (blue curve in Fig. 3.11-7). This is associated with low temperatures, likely due to the multiple tropical volcanic eruptions that occurred during this period (Tierney et al., 2015), as can be seen in Fig. 3.4. The values of $\delta^{18}\text{O}$ then gradually decreases to reach their lowest level at the end of the 20th century,

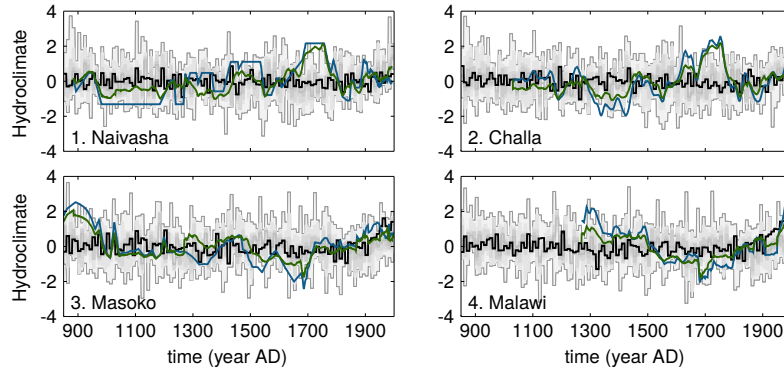


Figure 3.10 – Evolution of lake-based hydroclimate throughout the last millennium at the four continental sites considered (see Fig. 3.1), according to the first nine ensemble members of the CESM-LME (black curve is the mean surrounded by the ensemble range in grey), the proxy-based reconstructions described in Section 3.2.4 (in blue), and the data-assimilated model output (in green). The axes are oriented such that wetter conditions point upward.

Table 3.2 – RMSE between simulated and reconstructed time series without (third column) and with (fourth column) data assimilation, at each East African site considered.

id	Site	RMSE: data vs model output (ensemble mean)	RMSE: data vs data-assimilated model output	Difference (in %)
1	Naivasha	1.08	0.62	–43.05
2	Challa	1.10	0.57	–57.08
3	Masoko	0.62	0.47	–47.40
4	Malawi	0.43	0.58	–57.74

following the warming of the Indian Ocean. This decreasing trend is observed in all reconstructions, although it is less marked in Mentawai. The ensemble mean of the simulations without data assimilation (black curves in Fig. 3.11) usually agrees with these reconstructed downward trends, although the simulated trend is less pronounced. Both reconstructed and simulated changes in coral $\delta^{18}\text{O}$ show a relatively high variability at the interannual time scales, but as can be expected, the temporal changes do not coincide.

Data assimilation improves the consistency between reconstructed and simulated time series (green curves in Fig. 3.11), as shown by the smaller

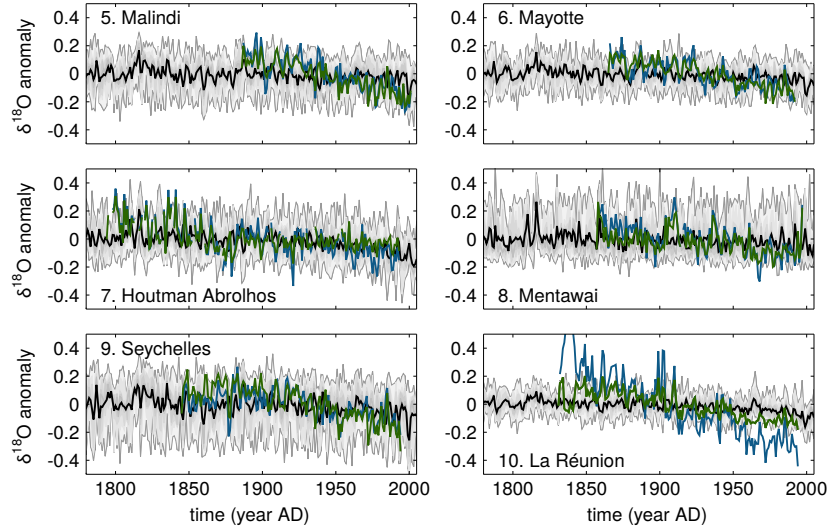


Figure 3.11 – Evolution of coral $\delta^{18}\text{O}$ throughout the last two centuries at the six oceanic sites considered (see Fig. 3.1), according to the first nine ensemble members of the CESM-LME (black curve is the mean surrounded by the ensemble range in grey), the proxy-based reconstructions described in Section 3.2.4 (in blue), and the data-assimilated model output (in green). Results are shown as anomalies with respect to the whole period covered.

values of RMSE after assimilation (Table 3.3). The biggest improvement is achieved at Malindi, where data assimilation allows matching very well the observed interannual changes. Data assimilation also makes the simulated trends over the last two centuries closer to the reconstructed ones, although the slope is still too weak in La Réunion.

Data assimilation provides thus skillful local reconstructions compared to the time series that are assimilated, which is the minimum requirement. The goal here is to obtain spatial reconstructions of precipitation and SSTs, whose skill will depend on the propagation of the information contained in the ten proxy-based reconstructions considered. There is no spatial proxy-based reconstruction available over the full period investigated that would allow assessing the skill of our reconstructions. Hence, it is achieved here by comparing our results with the observational data sets ERSST-v4 and GPCC-v7, over the 20th century (Fig. 3.12).

Table 3.3 – RMSE between simulated and reconstructed time series without (third column) and with (fourth column) data assimilation, at each oceanic site considered.

id	Site	RMSE: data vs model output (ensemble mean)	RMSE: data vs data-assimilated model output	Difference (in %)
5	Malindi	0.123	0.052	−58.00
6	Mayotte	0.096	0.055	−42.51
7	Houtman Abrolhos	0.124	0.053	−56.92
8	Mentawai	0.120	0.054	−54.89
9	Seychelles	0.106	0.071	−32.78
10	La réunion	0.222	0.168	−24.36

The skill of the reconstruction of rainfall performed by assimilating hydroclimate is limited, with only a thin strip of slightly positive CE observed in East Africa, containing the lakes Masoko and Malawi (Fig. 3.12). However, these positive CE are actually due to the common recent trend between simulated and observed hydroclimate rather than to the data assimilation process. The data set for rainfall covers only the land-surface, which prevents the estimation of the reconstruction skill over the Indian Ocean. Nevertheless, it is likely close to zero or even negative as deduced from the experiments performed in an idealized framework. As expected again from the pseudo-proxy experiments, the assimilation of hydroclimate does not lead to any skill in reconstructing SSTs. The skill of the reconstruction of Indian Ocean SSTs is, to some extent, higher when assimilating coral $\delta^{18}\text{O}$, with positive CE in the north of the ocean as well as along the east coast of Africa, an area that includes three sites where data is assimilated, ie. Malindi (id 5), Mayotte (id 6) and the Seychelles (id 9). However, the latter experiment does not allow to obtain skillful reconstructions of rainfall over Africa, and the CE of the reconstructions of SSTs are negative in a large part of the Central and Eastern Indian Ocean.

The lack of skill even at some of the record sites may seem surprising at first sight. Indeed, the data assimilation process is able to bring the simulated hydroclimate and coral $\delta^{18}\text{O}$ close to the proxy time series (Fig. 3.10 and 3.11), as shown by the decreased RMSE. Furthermore, measured coral $\delta^{18}\text{O}$ and hydroclimate-related proxy records should be, by construction, closely related to local SST and rainfall, respectively. However, the correlation coefficients between observed decadal rainfall and proxy-based reconstructed hy-

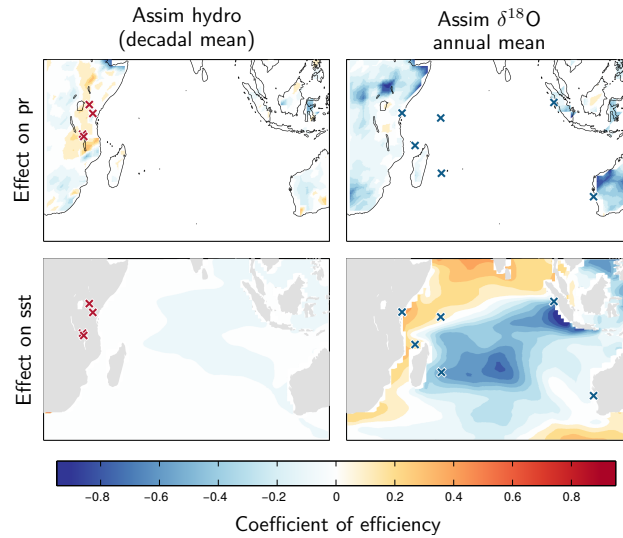


Figure 3.12 – Coefficients of efficiency computed from the difference between the CESM-LME with data assimilation of the real-world proxy-based reconstructions and the data sets ERSST-v4 (for SSTs) and GPCC-v7 (for rainfall, only covering the land-surface) over the period 1900-2005 AD, using 2079 particles. The two left panels show the coefficients of efficiency based on the reconstructions of decadal mean rainfall and SSTs from the experiments with data assimilation of the four hydroclimate results only, and the two right panels show the coefficients of efficiency based on the reconstructions of annual mean rainfall and SSTs from the experiments with data assimilation of the six coral $\delta^{18}\text{O}$ time series only. The crosses indicate the locations where data are assimilated, and are red in case of hydroclimate and blue in case of coral $\delta^{18}\text{O}$.

droclimate at the four East African sites are weak (not shown). This is probably due to the quite indirect nature of the link between the hydroclimate-related reconstructed and simulated variables. Indeed, the model variable is smoothed precipitation minus evaporation while the reconstructed hydroclimate variables depend on numerous other elements such as the inflow and outflow from and to rivers, surface runoff and ground water, the evaporation from the lakes, as well as interactions with the aquifer (e.g. Becht and Harper, 2002), that may obscure the signal brought by actual precipitation minus evaporation. Actually, the skillful reconstructions of rainfall in a few locations of East Africa is attributable to a common trend that exists between the observed

and the simulated rainfall time series (not shown), rather than to the data assimilation process.

The negative CE at some of the oceanic records cannot be explained by a low correlation between SSTs and coral $\delta^{18}\text{O}$. Indeed, although other environmental variables also play a role, the relationship between those two variables is robust and well-known (e.g. Brown et al., 2006; Stevenson et al., 2013). However, the coefficient binding the two variables in Equation 3.1 may vary significantly from site to site (Evans et al., 2000). In our data assimilation experiment, we have applied at each location the value of $-0.22\text{‰}\cdot^{\circ}\text{C}^{-1}$, as proposed in Thompson et al. (2011) as a mean estimate. Ideally, the forward model should be calibrated at each individual site. However, this requires to take into account changes in SSS, while there is no reliable instrumental data set of salinity for the whole period considered. The changes in SST dominate on changes in SSS to produce the coral $\delta^{18}\text{O}$. Hence, the impact of a local calibration is investigated here by estimating coral $\delta^{18}\text{O}$ from model results using a linear regression based on local observed SSTs from the instrumental data set ERSST-v4, instead of the forward model proposed in Thompson et al. (2011). In this case, the error considered in the data assimilation process is different at the six records sites depending on the regression model. This was not the case in the experiments using the forward model where only the error of the measurement is considered, while the error related to the relationship between coral $\delta^{18}\text{O}$ on the one hand and SST and SSS on the other was neglected.

This approach allows having skillful reconstructions of SSTs over the Indian Ocean (Fig. 3.13). However, as might be expected, the skill is not as high as when assimilating instrumental observations (Fig. 3.8), with a mean CE over the Indian Ocean of 0.19 instead of 0.32. Also, as in the previous experiments, the representation of precipitation on land is not improved.

3.5 Discussion and conclusions

The focus of this paper is to improve reconstructions of the East African rainfall and Indian Ocean SSTs based on their covariance. This is achieved by means of an off-line method of data assimilation, using the recently available ensemble of last millennium simulations performed with the model CESM1. Hydroclimate-related records at four East African sites, Lake Naivasha, Lake

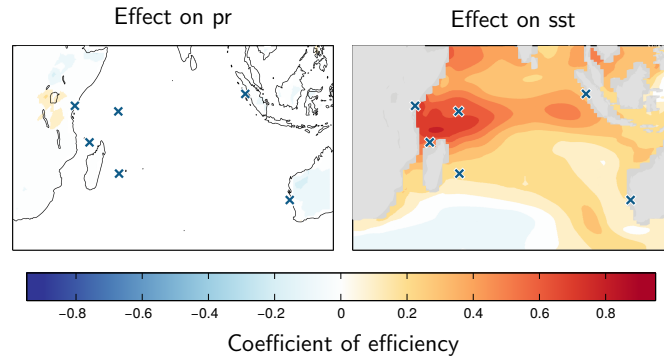


Figure 3.13 – Coefficients of efficiency computed from the difference between rainfall (a.) and SSTs (b.) of CESM-LME with data assimilation of measured coral $\delta^{18}\text{O}$ and the data sets GPCC-v7 (for rainfall, only covering the land-surface) and ERSST-v4 (for SSTs). The period covered is 1900–2005 AD. The ensemble size is 2079. During the data assimilation process, the model coral $\delta^{18}\text{O}$ is induced from the parameters of the linear regression computed between measured coral $\delta^{18}\text{O}$ and local observed SSTs (data set ERSST-v4). The CE are computed from annual mean results. The crosses indicate the locations where data are assimilated, and are red in case of hydroclimate and blue in case of coral $\delta^{18}\text{O}$.

Challa, Lake Malawi and Lake Masoko, as well as SSTs-related records at six oceanic sites spread over the Indian Ocean, are selected as constraints for the assimilation.

The assimilation of pseudo-proxy data derived from the tenth ensemble member of the CESM-LME allows having skillful reconstructions of the Indian SSTs based on the East African rainfall, and vice versa. The reconstructions obtained when assimilating both variables basically combine the benefits obtained in each single-variable assimilation experiment. The quality of the reconstructions is however strongly dependent on the number of particles considered. Only using 9 particles is usually not sufficient to spread spatially the information contained in the record sites selected. Hence, most reconstructions based on data assimilation showed in this paper use more particles than actually available for each year of assimilation, by also selecting particles belonging to other years than the one considered. This increases the range of possible climate states and thus allows improving the agreement between the data-assimilated model output and the data. Beyond 99 particles, however, the

improvement brought by further increasing the size of the ensemble becomes modest in our experimental set up.

The four East African records selected for the assimilation do not contribute equally in providing skillful reconstructions of the East African rainfall and of Indian SSTs. Indeed, precipitation over the lakes Masoko and Malawi appears to be isolated from the large-scale since neither the assimilation of Indian SSTs nor the assimilation of rainfall further north in East Africa provides skillful reconstruction of rainfall over these sites, and conversely. Hence, Challa and Naivasha are much better candidates to reconstruct large-scale patterns of climate than Masoko and Malawi, according to the physics of CESM1. This heterogeneity is consistent with the very different patterns of correlations between East African rainfall and Indian Ocean SSTs obtained when considering the rainfall averaged, on the one hand, over the region including Challa and Naivasha, and on the other hand, over the region containing Masoko and Malawi (Klein et al., 2016). This may appear contradictory with the recent study of Nicholson (2014), who shows that changes in the East African rainfall over the last two centuries are relatively coherent over the region. The latter study is based on a principal component analysis, the objective of such tool being to highlight common patterns of variability. Here, we suggest that the common signals in the East African rainfall found in Nicholson (2014) do not explain a fraction of the total variance that is large enough to obtain skillful reconstruction of rainfall over an area of East Africa based on the rainfall over another area.

Unfortunately, reconstructing Indian SSTs based on the East African rainfall or the East African rainfall based on Indian ocean SSTs is only possible in idealized conditions when the model physics is supposed to be perfect. If the pseudo-proxies are derived from another model, this ability is lost because of the differences in model physics. This is also the case if real observations are used. Furthermore, assimilating precipitation no more improves regional rainfall, but only local precipitation. In contrast, these experiments show that a reconstruction of the whole Indian Ocean SSTs can be obtained by only assimilating the SST results of six sites spread over the Ocean. However, this does not constrain enough the evolution of the East African rainfall. The representation of the covariance of the Indian Ocean SSTs seems thus to be relatively consistent among models and between models and recent instrumental data sets, unlike the one between the East African rainfall at different locations and

of the teleconnection between the two variables. In addition to the different patterns associated with the modes of natural variability in models and observations, this may be related to the differential impact of volcanic events and, to a lesser extent, of anthropogenic forcings, on the variables assimilated. In the reconstructions based on the assimilation of SSTs results, most large eruptions are followed by similar changes in the pattern of SSTs that go beyond the natural variability. In contrast, if there is an effect of the eruptions on the East African hydroclimate, it is not visible in our experiments, meaning that the effect of the volcanism on the East African hydroclimate does not overwhelm the internal variability.

Assimilating real proxy-based reconstructions is not straightforward, given that the physical quantity that is reconstructed from proxy records is not directly simulated by the climate model. Here, the model variables are processed to match the reconstructed variables as closely as possible. For oceanic records, it is done through the use of a linear bivariate model that computes the model coral $\delta^{18}\text{O}$ based on simulated SSS and SSTs (Thompson et al., 2011). This is harder for the East African hydroclimate proxy records, since the variables reconstructed as well as the lakes from which they originate are different. However, all proxy-based reconstructions can be qualitatively interpreted as smoothed versions of local-moisture balance, that is translated in the model by smoothed precipitation minus evaporation. Within the ideal framework considering the assimilation of the results of the tenth ensemble member of the CESM-LME, assimilating these model versions of the reconstructed variables has only little impact on the quality of the reconstructions of rainfall and of SSTs, the overall spatial patterns of the reconstructions skill being similar than when assimilation rainfall and SSTs.

The situation is different with real proxy-based reconstructions. The assimilation technically works: compared to the model ensemble mean, the model results with data assimilation are characterized by strongly decreased RMSE with the reconstructed or measured time series at all record sites selected. However, the skill of the resulting reconstructions, as derived from recent instrumental data set, is limited. A first issue for the experiments with data assimilation of hydroclimate-related records is the very indirect link between the proxy-based reconstructed variables and the model version of these variables. But even if the discrepancy was reduced, this experiment is not ex-

pected to bring skillful spatial reconstructions of SSTs or even of rainfall, as deduced from pseudo-proxies experiments.

Assimilating coral $\delta^{18}\text{O}$ is a priori more straightforward. A simple and robust forward proxy model can be used to estimate this variable from model results, which allows a meaningful comparison with proxy records. However, using the forward model with standard (spatially constant) coefficients provides SST reconstructions with only modest skill. The issue here is that the relationship between coral $\delta^{18}\text{O}$ and SSTs varies between the individual sites. When this spatial variability is taken into account, skillful reconstructions of the SSTs over the whole Indian Ocean can be achieved with the assimilation of only six records, such as when assimilating pseudo-proxies, but this does not lead to a better representation of the East African rainfall compared to the model mean.

Two critical points that tend to decrease the capacity to obtain skillful reconstructions have thus been highlighted in this study. First, the biases in the physics of the model do not allow to take advantage of the correlation between SSTs and precipitation. By construction, the data assimilation method employed in this study leads to reconstructions that are consistent with the physics of the model used, ie. CESM1. However, all climate models show very different teleconnections between the East African rainfall and tropical SSTs. Although CESM1 is one of the closest to the observations regarding this diagnostic over the recent past (Klein et al., 2016), the differences between the observed and simulated teleconnection is still large, as demonstrated by the much poorer reconstructions achieved when assimilating recent observations compared to the assimilation of the tenth ensemble member of the CESM-LME. The results of this study highlight the importance of the model errors, showing the strong relevance to continue improving the GCMs. This appears particularly critical for precipitation, the simulation of SST covariance being already good enough to provide useful information for the reconstruction of this variable. The second critical point is the interpretation of the proxy-records in order to have a coherent model-data comparison. The variables that are included in climate models are often different from the ones reconstructed from proxy records, and the link between simulated variables and proxy may vary significantly between locations. Hence, the effort to reconcile both sources of information, for instance through forward modelling, has to be pursued.

CHAPTER

**MECHANISMS EXPLAINING THE
LINKS BETWEEN INDIAN OCEAN
SSTs AND THE EAST AFRICAN
RAINFALL: A SENSITIVITY STUDY
WITH THE CLIMATE MODEL
EC-EARTH**

Abstract

This study assesses the impact of two different patterns of Indian Ocean SST anomalies on the East African rainfall, using sensitivity experiments with the fully coupled GCM EC-EARTH. The first pattern consists in higher SSTs in the western tropical Indian Ocean, and the second in a higher gradient of SSTs between the western and the eastern tropical Indian Ocean, with warmer surface water in the west and cooler in the east. Although higher western Indian Ocean SSTs can, alone, lead

90 Link between Indian Ocean SST patterns and East African rainfall

to a slight increase in the East African rainfall, the effect of the enhanced gradient of SSTs on the precipitation over East Africa is much higher. This is related to a reorganization of the surface winds with low-level easterly anomalies over the tropical Indian Ocean and weak westerly anomalies over equatorial central and eastern Africa, that is present only in the simulation with a prescribed enhanced SST gradient. These wind anomalies create a convergence zone over the East African region, associated with ascending motion and increased convective activity.

4.1 Introduction

IT has been observed that enhanced rainfall during the short rains in East Africa is associated with positive SST anomalies in the western Indian Ocean and negative anomalies in the eastern Indian Ocean, pattern that resembles a positive phase of the IOD (e.g. Clark et al., 2003; Black et al., 2003; Ummenhofer et al., 2009). As seen in the general introduction and in the introduction of Chapter 3, this relationship has been highlighted in many studies using various statistical methods. Most of these studies discuss hypotheses about the physical processes involved in this link, but the statistical methods do not allow identifying precisely and directly the underlying mechanisms.

To achieve this, a systematic assessment of the potential factors driving the observed relationship between the Indian Ocean SST pattern and the East African rainfall is needed. This can be done by performing sensitivity experiments using climate models specifically designed for that purpose. In this framework, Goddard and Graham (1999) have assessed the relative contribution of the Indian and the Pacific Oceans to the rainfall variability over East Africa, among other regions. They performed several model experiments with the atmospheric general circulation model (AGCM) ECHAM3.2 (Roeckner et al., 1992), in which the atmosphere is forced by realistic SST anomalies globally, only in the Indian Ocean basin and only in the tropical Pacific. They found that, although the Pacific plays a role, it is the Indian Ocean variability that is essential to reproduce well the observed rainfall variability over eastern Africa. In the simulation forced by anomalous SST in the Indian Ocean only, positive SST anomalies in the western tropical Indian Ocean drive convergent westerlies over East Africa, which enhances moisture flux and leads to more convection over the region. Similar results were found in Latif et al. (1999), who have investigated using the same AGCM the origin of the eastern equatorial African positive rainfall anomalies during December-January 1997/98, a period characterized by a strong El Niño event (Fig. 1.3). More recently, Ummenhofer et al. (2009) have studied the link between enhanced East African rainfall in October-November, the so-called short rains, and different configurations of Indian Ocean SST pattern, using the GCM CCSM3 (Collins et al., 2006), run in the atmosphere-only mode. Consistently with the previous studies, they found that the major factor driving positive rainfall anomalies is the warm waters in the western Indian Ocean. Indeed, abnormally high west-

ern Indian Ocean SSTs are sufficient to induce a local reduction in sea level pressure, that is associated with converging wind anomalies over East Africa, leading to increased convective activity over the region (Ummenhofer et al., 2009).

The above studies thus agree on the major and direct role of the western Indian Ocean SSTs in driving the East African rainfall variability, while the eastern Indian Ocean SSTs and the Pacific variability are suggested to be of less importance. However, this conclusion is only based on two different AGCMs. Yet GCMs widely differ in their representation of the teleconnections between the East African rainfall and tropical SSTs, only a few being approximately in agreement with recent instrumental data sets (Chapter 2). The goal of this chapter is to confirm or infirm the above conclusion, by performing sensitivity experiments with the fully coupled GCM EC-EARTH (Hazeleger et al., 2012), that simulates very realistically the interannual link between East African rainfall and Indian SSTs. Specifically, we investigate which of the following two Indian Ocean SST anomalies configurations leads to the largest increase in the East African rainfall, and why. In the first configuration, only the western Indian Ocean surface is artificially warmed. In the second one, the western Indian Ocean surface is also warmed, but to a lesser extent, and the eastern Indian Ocean surface is cooled down, which creates a dipole pattern resembling a positive phase of the IOD.

This chapter is structured as follows. The next section describes the model used, its performance over the recent past, and the design of the two sensitivity experiments. Section 4.3 shows the changes in SSTs and rainfall patterns prescribed in the two sensitivity experiments. Section 4.4 investigates the processes involved in the changes of rainfall patterns, and, finally, Section 4.5 presents a summary of the main findings and some concluding remarks.

4.2 Methodologies

4.2.1 Model description

The experiments have been performed with the state-of-the-art numerical earth system model EC-EARTH (Hazeleger et al., 2012), version 3.1. Its atmosphere model is the Integrated Forecasting System (IFS), developed by the European Centre for Medium-Range Weather Forecast (ECMWF).

A detailed description of the dynamics and physics of IFS can be found at: <http://www.ecmwf.int/en/forecasts/documentation-and-support/changes-ecmwf-model/ifs-documentation>. The horizontal resolution of this model, in the configuration selected here, corresponds to about $0.7^\circ \times 0.7^\circ$ latitude-longitude, with 11 vertical levels up to 10 hPa. The land surface component is an improved version of the Tiled ECMWF Scheme for Surface Exchanges over Land (H-TESSEL; Balsamo et al., 2009), that is directly integrated into IFS. The ocean is simulated by the GCM Nucleus for European Modelling of the Ocean (NEMO), version 2 (Madec, 2008), that is coupled to the Louvain-la-Neuve Ice Model version 2 (LIM2) sea ice model (Fichefet and Maqueda, 1997). The grid used for the ocean and the sea ice is ORCA3.2, corresponding to an horizontal resolution of about 1 degree and 42 levels of depth. The IFS/H-TESSEL and NEMO/LIM2 components are coupled by the Ocean Atmosphere Sea Ice Soil version 3 (OASIS3; Valcke, 2006) coupler. Details of the model components and their coupling can be found in Hazeleger et al. (2012).

4.2.2 Performance of EC-EARTH over the recent past

4.2.2.1 Mean seasonal cycle of precipitation

EC-EARTH is able to simulate the bimodal cycle of rainfall observed in Equatorial East Africa (Fig. 4.1-a). The long rains are underestimated, but this is the case for all GCMs (e.g. Yang et al., 2015, Chapter 2). Furthermore, the unimodal cycle of rainfall observed in southeastern Africa is also well simulated (Fig. 4.1-b). The influence of the forcings on these seasonal patterns seems weak, as suggested by the very similar curves obtained in the preindustrial control run and in an experiment of EC-EARTH driven by time-evolving forcings over the years, which uses the version 2.3 of the model.

4.2.2.2 Mean seasonal cycle of the Indian Ocean SSTs

The control simulation performed with the version of EC-EARTH used in this study (version 3.1) shows a very similar seasonal cycle of SSTs in the western Indian Ocean than the observations over the 20th century, although it has a very slight cold bias during the warmer season (from December to May, Fig. 4.2-a). In the eastern Indian Ocean, the amplitude of the cycle of SSTs is over-

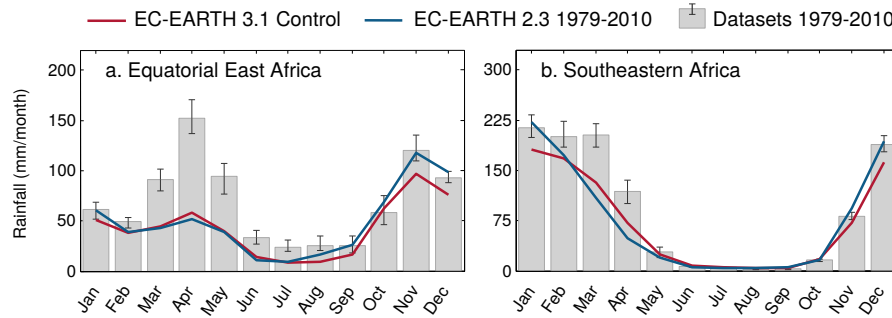


Figure 4.1 – Mean monthly rainfall over Equatorial East Africa (a., bounded by the coordinates 4.8°S to 0.2°N and 34.2 to 40.2°E) and over Southeastern Africa (b., delimited by the coordinates 7.2 to 12.2°S and 31 to 37°E) in observations (bar plots) and in two versions of EC-EARTH (curves). The period considered for the observations and for EC-EARTH 2.3 is 1979-2005. The observation values are based on the average of four instrumental datasets (GPCC-v6 (Schneider et al., 2014), GPCP-v2.2 (Huffman et al., 2009), CMAP (Xie and Arkin, 1997) and PREC/L (Chen et al., 2002)), whose range is represented by error bars.

estimated in the same simulation, and the SSTs are slightly lower compared to the recent observations. (Fig. 4.2-b). This difference is not surprising: the forcings are kept fixed at their preindustrial level in the control simulation, while the anthropogenic forcing has warmed the SSTs over the last decades (see Fig. 2.5). EC-EARTH 3.1 seems thus to perform relatively well in simulating the Indian Ocean seasonal cycle.

The transient simulation of EC-EARTH (version 2.3) appears to have a more realistic seasonal cycle of SSTs over the eastern Indian Ocean compared to the control simulation, but shows a similar cold bias (Fig. 4.2-b). Surprisingly, the cold bias is more pronounced in the transient simulation than in the control simulation in the western Indian Ocean (Fig. 4.2-a), while the former simulation takes into account the anthropogenic forcing. In this case, the changes operated between the models version has thus a significant impact on the results.

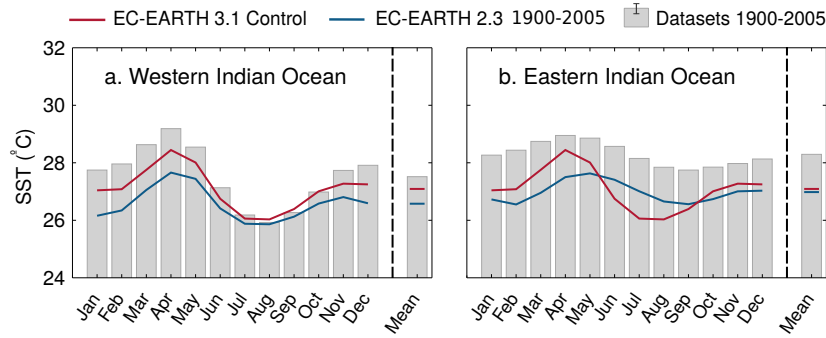


Figure 4.2 – Mean seasonal cycle of SSTs over the western (-8 to 2°N and 40 to 65°E ; a.) and the eastern (-10 to 0°N and 80 to 105°E ; b) Indian Ocean in observations (bar plots, average of the datasets ERSST-v3b (Smith et al., 2008) and HadSST3 (Kennedy et al., 2011a,b)) and in two versions of EC-EARTH (curves). Only the first ensemble member of each GCM is used (r1i1p1). The period considered for the observations and for EC-EARTH 2.3 is 1900-2005.

4.2.2.3 Large-scale tele-connections

Regarding the link between the East African rainfall and Indian Ocean SSTs, the correlation coefficients pattern between those two variables as simulated by EC-EARTH is the closest to the observations compared to six other GCMs analyzed in Chapter 2 (Fig. 4.3), which makes this model well suited for the analyses performed in this study. In this case, the effect of the recent forcings and of the model version seems limited, given the similar results obtained in the control run and in the forced run over the period 1950-2005.

As expected, the correlations between the observed East African rainfall and Indian Ocean SSTs strongly vary over the year. The strongest values are found during the short rains, in OND, which is consistent with observations. During this season, a dipole is clearly observed in the Indian Ocean, with positive correlations in the west and negative ones in the east. These correlation coefficients are statistically significant according to t tests. The boreal winter (JFM) is characterized by positive and significant correlations over the whole Indian Ocean, while the link between the East African rainfall and Indian Ocean SSTs is weak or non-existent during the boreal spring (AMJ) and summer (JAS). All of these patterns are relatively well simulated by EC-

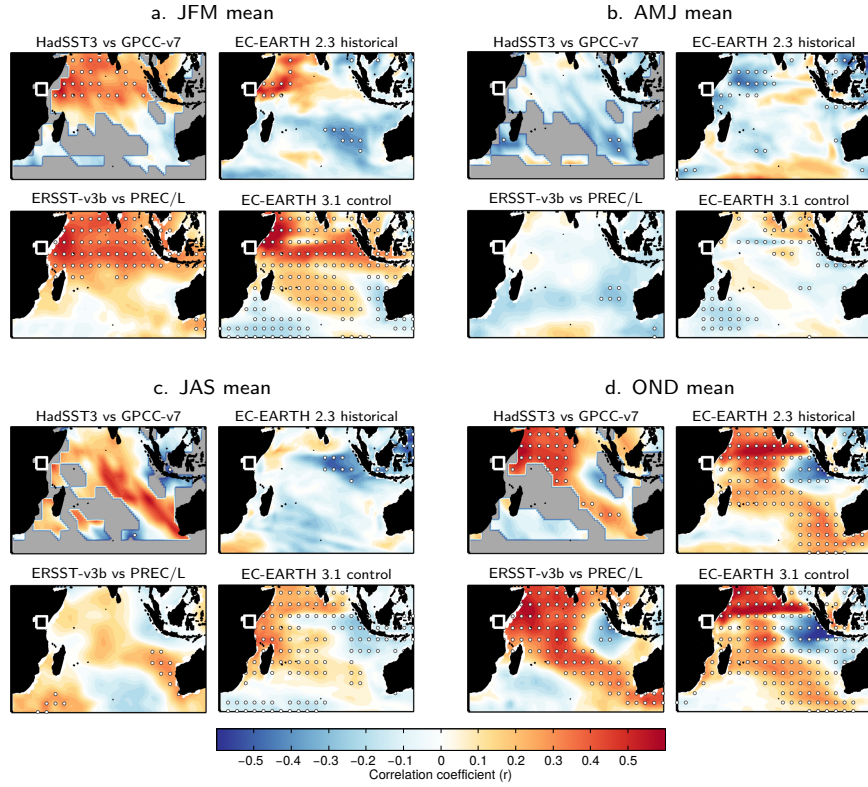


Figure 4.3 – Pearson correlation coefficients between mean seasonal rainfall over the Equatorial East Africa (4.8°S to 0.2°N and 34.2 to 40.2°E, white frame) and Indian SSTs in observations and in two versions of the model EC-EARTH for the period 1950-2000. In areas overprinted with white circles, a null hypothesis of no correlation can be rejected at the 5% level. No data are available from grey areas.

EARTH, although differences are present especially when the correlations are low.

4.2.3 Sensitivity experiments

Two sensitivity experiments are analyzed in this paper, and compared to a control run. The latter consists in the average of ten 30-year long simulations using preindustrial initial conditions. The initial conditions of those ten runs are based on the results of a 100 year-long preindustrial control

run performed on our computer. This experiment is itself initialized from a 1800 year-long preindustrial control run performed by Paolo Davini (Institute of Atmospheric Sciences and Climate, Italy), whose restarts are available online at http://sansone.to.isac.cnr.it/ecearth/init/year1850_tome/15010101/. To have different realisation of the ten 30 year-long simulations, a gaussian noise with a standard deviation of 0.0001°C is added to the SSTs at the start of each experiment.

For the two sensitivity experiments, height ten year-long simulations using the same initial conditions as the preindustrial control runs of 30 years have been performed. In this study, we discuss the average over these height experiments, in order to maximize the signal associated with the response to the perturbation rather than to the natural variability of the system. In the first sensitivity experiment, called WST, a constant artificial flux of 100 W.m^{-2} is applied at the ocean surface in the area of the western Indian Ocean bounded by the coordinates -8 to 2°N and 40 to 65°E . In the second experiment, called BIP, the same area in the western Indian Ocean SSTs is warmed up by a constant flux of 50 W.m^{-2} , while the Eastern Indian Ocean included between the coordinates -10 to 0°N and 80 to 105°E is cooled down by applying a surface heat flux of -50 W.m^{-2} . Hereafter in the Chapter, western Indian Ocean and eastern Indian Ocean refer to the regions defined above. The boundaries of those two regions are drawn in all figures shown in this chapter.

4.3 Impact of the perturbation on SSTs and rainfall

4.3.1 Simulated SST anomalies

The constant perturbation of 100 W.m^{-2} leads to a local increase in SST of 0.75°C in average over the area where the perturbation is applied (Fig. 4.4-a). Within this area, the SSTs are quickly adjusted to the perturbation, and appear to be already at the equilibrium after one month, as shown by the relatively stable time series if seasonal variation is removed (red curve in Fig. 4.4-a). The warming is rapidly propagated to the whole Indian Ocean, except its southwestern part, and the SST anomaly patterns are very similar each year of the experiment (not shown), highlighting that the simulation is in a quasi-equilibrium.

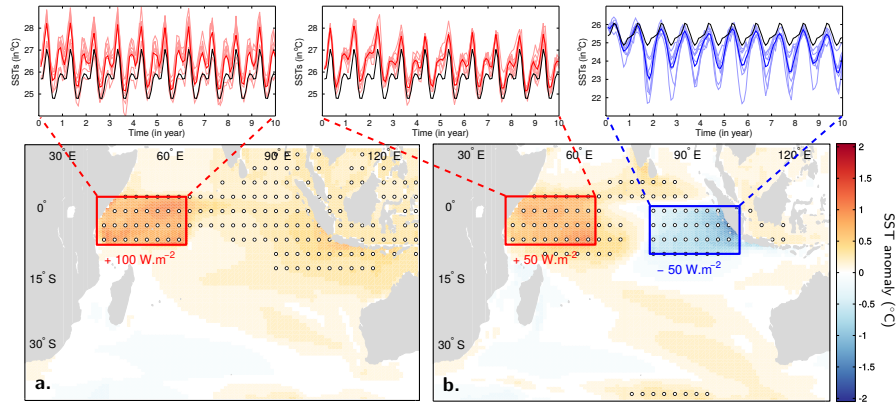


Figure 4.4 – a. Spatial annual mean SST anomalies in the WST experiment, with the time series of the 8 WST experiments (light red), their mean (dark red), and the mean annual cycle of the control runs (black) averaged over the box in which the perturbation of 100 W.m^{-2} is applied. **b.** Same as in a., but for the BIP experiment, with the addition of the time series corresponding to the average of SSTs over the box where a negative flux of -50 W.m^{-2} is applied, that are shown in light blue while their mean in darker blue. The average annual cycle of the control run is drawn in black. In the spatial maps, the null hypothesis of no difference between the sensitivity experiments and the control run can be rejected at the 5% level in areas overprinted with white circles.

In the BIP experiment, the increase in SSTs associated with the perturbation of 50 W.m^{-2} is in average over the box where the flux is applied equal to 0.67°C (Fig. 4.4-b), ie. slightly smaller as in the WST experiment. Once again, the perturbation has a very rapid impact on the SSTs that appear at the quasi-equilibrium after less than one month. In the eastern Indian Ocean, the negative flux of -50 W.m^{-2} leads to a decrease in SST of about 0.69°C in average over the region where it is applied. In this case, one year is necessary for the SSTs to stabilize the difference between the sensitivity and the control experiments. Hence, in the following of the study, the first year of each sensitivity experiments is removed to make sure that the results analyzed are at the quasi-equilibrium.

Unlike in Goddard and Graham (1999), Latif et al. (1999) and Ummenhofer et al. (2009) which performed sensitivity experiments by forcing their atmosphere model with realistic SST variability, the simulated changes in SSTs are induced here indirectly by a external forcing. This forcing has to be strong

enough to generate substantial changes in the SSTs in order to detect their impact, but not too strong so that the patterns obtained are close enough to situations that might occur in the real world, as simulated by EC-EARTH.

In the WST experiment, the 100 W.m^{-2} imposed on the western Indian Ocean induces an increase of the annual mean SSTs over the region corresponding to a bit more than three standard deviations of the control run, as can be seen in Fig. 4.5-a. In the BIP experiment, the annual mean change in the western Indian Ocean SSTs resulting from the positive flux of 50 W.m^{-2} is larger than three standard deviations of the control run (Fig. 4.5-a). In contrast, the decrease in SST in the eastern Indian Ocean due to the flux of -50 W.m^{-2} falls within the range of the distribution of the annual mean SSTs of the control run. It still corresponds to a rare event since it is 2.5 standard deviations away from the average of the distribution (Fig. 4.5-b). Finally, the gradient of SST between the western Indian Ocean and the eastern Indian Ocean obtained by the combination of both perturbations represents a very unusual case since it exceeds 4 standard deviations from the average (Fig. 4.5-c).

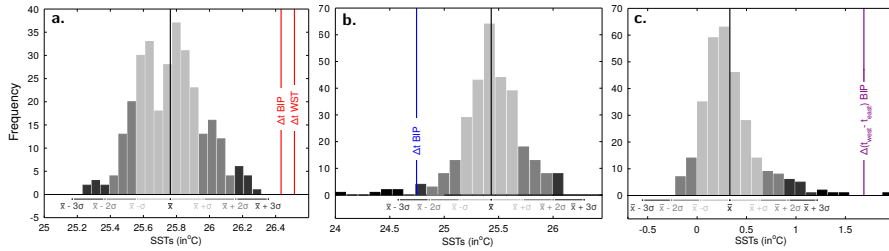


Figure 4.5 – Frequency distributions of annual mean SSTs in the control simulation averaged over the western Indian Ocean (a.), the eastern Indian Ocean (b.), and the difference between the western and the eastern areas (c.). The vertical black lines are the averages of the distributions. The bars representing the samples of the distributions are colored as a function to their distances to the averages, as computed in standard deviation. If they are smaller than the average ± 1 standard deviation, they are colored in light gray, between the average ± 1 and 2 standard deviations, they are colored in a darker gray, and beyond the average ± 2 standard deviations, they are colored in a very dark gray. The vertical colored lines show the annual mean SST changes in the sensitivity experiments.

The changes in annual mean SST obtained in the two sensitivity experiments thus generally fall at the edge or slightly beyond the variations driven by natural variability as simulated in the control run of EC-EARTH. The re-

quirements of the experimental design are thus fulfilled. Furthermore, the resulting gradient is of the same order of magnitude as the one obtained in the observations during years characterized by a strong positive phase of the IOD (not shown).

The link between the East African rainfall and Indian SST is strongest during the short rains, ie. during OND (Fig. 4.3). Hence, in addition to the annual mean values, this study will also focus on the results averaged over this period. In the WST experiment, the OND mean SSTs increase by about 0.90°C in the western Indian Ocean, while in the BIP experiment, the increase is of about 0.68°C in the same area and the SSTs decrease by about 1.11°C in the eastern Indian Ocean (Fig. 4.6). This is thus very similar than the annual mean values, although the changes are slightly larger during this season. Actually, the changes in surface temperature due to the perturbations are relatively homogeneous over the year in the two Indian Ocean study areas selected (Fig. 4.4), which is not surprising given that the perturbation is constant throughout the year.

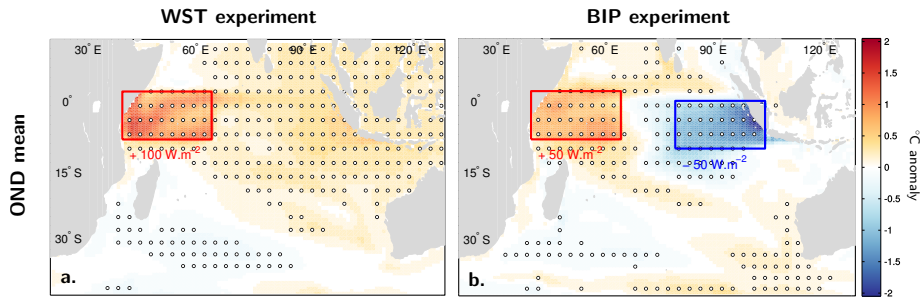


Figure 4.6 – Spatial OND mean SST anomalies in the WST (a.) and in the BIP (b.) experiments. The null hypothesis of no difference between the sensitivity experiments and the control run can be rejected at the 5% level in areas overprinted with white circles.

4.3.2 Simulated rainfall anomalies

Overall, the higher (lower) SSTs are, as expected, associated to increased (decreased) local rainfall (Fig. 4.7). In the WST experiment, an increase in annual mean rainfall of over $44 \text{ mm} \cdot \text{month}^{-1}$ is observed in the western Indian Ocean. Interestingly, the increase in rainfall in the western Indian Ocean is larger in

the BIP experiment, reaching 74 mm.month^{-1} . As this area is characterized by a more modest increase in SST, this suggests a contribution of large-scale processes in addition to the local convective rainfall. The decrease in rainfall in the eastern Indian Ocean due to cooler surface water is of about 70 mm.month^{-1} in average.

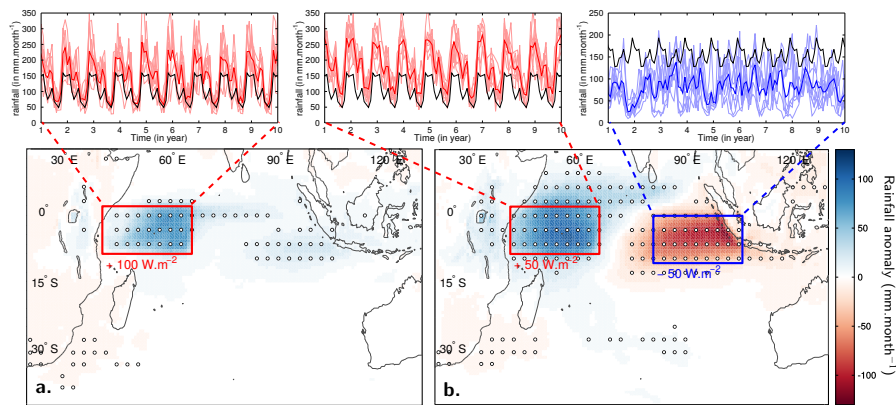


Figure 4.7 – a. Spatial annual mean rainfall anomalies in the WST experiment, together with the time series of the 8 WST experiments (light red), their mean (dark red), and the mean annual cycle of the control runs (black) averaged over the box in which the perturbation of 100 W.m^{-2} is applied. **b.** Same as in a., but for the BIP experiment, and with the addition of the time series corresponding to the average of rainfall over the box where a negative flux of -50 W.m^{-2} is applied, that are shown in light blue while their mean in darker blue. The average annual cycle of the control run is still drawn in black. In the spatial maps, the null hypothesis of no difference between the sensitivity experiments and the control run can be rejected at the 5% level in areas overprinted with white circles.

Both sensitivity experiments lead to enhanced rainfall over East Africa. The increase in annual mean rainfall in the East African region bounded by the coordinates 10°S to 5°N and 30 to 40°E reaches 4 mm.month^{-1} and 17 mm.month^{-1} in the WST and BIP experiments, respectively. The dipole in SST thus drives a larger increase in the East African rainfall than the local positive SST anomalies. This increase in rainfall is not constant throughout the year (not shown). The changes are very weak in JAS, and reach a clear maximum during the months OND, with an increase of 8 mm.month^{-1} in the WST experiment and of 38 mm.month^{-1} in the BIP experiment (Fig. 4.8).

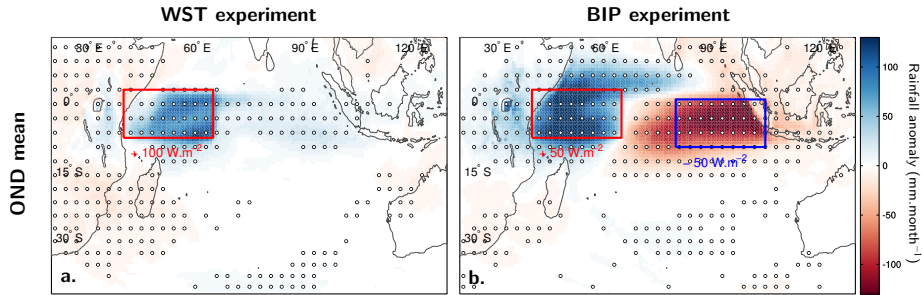


Figure 4.8 – Spatial OND mean rainfall anomalies in the WST (a.) and in the BIP (b.) experiments. The null hypothesis of no difference between the sensitivity experiments and the control run can be rejected at the 5% level in areas overprinted with white circles.

These increases in rainfall over the East African region are statistically significant, according to t tests. This means that the time series analyzed here are long enough to detect the influence of the perturbations. It is, however, interesting to compare these changes with the interannual variability of the East African rainfall. Is the magnitude of the changes induced by the imposed SST anomalies larger/smaller than the natural fluctuations of precipitation as measured by the variance of the control run? For the annually averaged changes, the increase in rainfall in East Africa in the WST experiment are smaller than 0.5 standard deviation of the rainfall time series of the control run (Fig. 4.9-a).

In the BIP experiment, the changes resulting from the perturbations are larger, with some areas in East Africa being characterized by an increase corresponding to between 0.5 and 1 standard deviation of the control run (Fig. 4.9-b). The increase in rainfall over East Africa is clearer when the results are averaged over the OND months. Although it does not exceed, except very locally, 1 standard deviation of the rainfall time series from the control run in the WST experiment (Fig. 4.9-c), much of East Africa is characterized in the BIP experiment by an increase in rainfall that strongly exceeds 1 standard deviation of the control experiment series (Fig. 4.9-d). Hence, according to the physics of EC-EARTH, if a dipole pattern of SSTs as in Fig. 4.6-b is observed in OND, there is great chance that the short rains will be unusually wet.

The enhanced East African rainfall appears thus predominantly driven by the gradient of SST between the western and the eastern Indian Ocean, rather

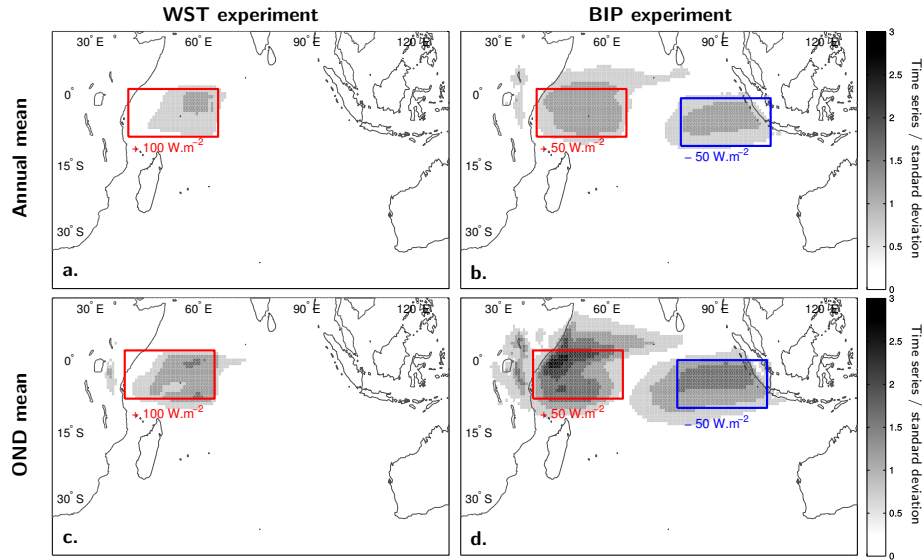


Figure 4.9 – Spatial annual and OND mean rainfall anomalies in the WST (left panels) and in the BIP (right panels) experiments, divided by the standard deviations of the control run .

than by local warmer SSTs, which contradicts the findings of Ummenhofer et al. (2009). In the next section, the cause of this behaviour is investigated by studying the processes responsible for these rainfall change patterns.

4.4 Causes of the simulated changes in rainfall

As one might expect, positive (negative) SST anomalies are accompanied with enhanced (decreased) local evaporation (Fig. 4.10). In the WST experiment, the western Indian Ocean is characterized, in average in the area where the perturbation is applied, by an annual mean increase in evaporation of 17 mm.month^{-1} (about 16 W.m^{-2}) compared to the control run (Fig. 4.10-a). As noticed for SSTs, the increase in annual mean evaporation is less marked in the BIP experiment, in which it reaches 13 mm.month^{-1} (12.3 W.m^{-2}) over the same area (Fig. 4.10-b). This mean annual pattern remains relatively constant all year long (not shown), including in OND (Fig. 4.10-c and d).

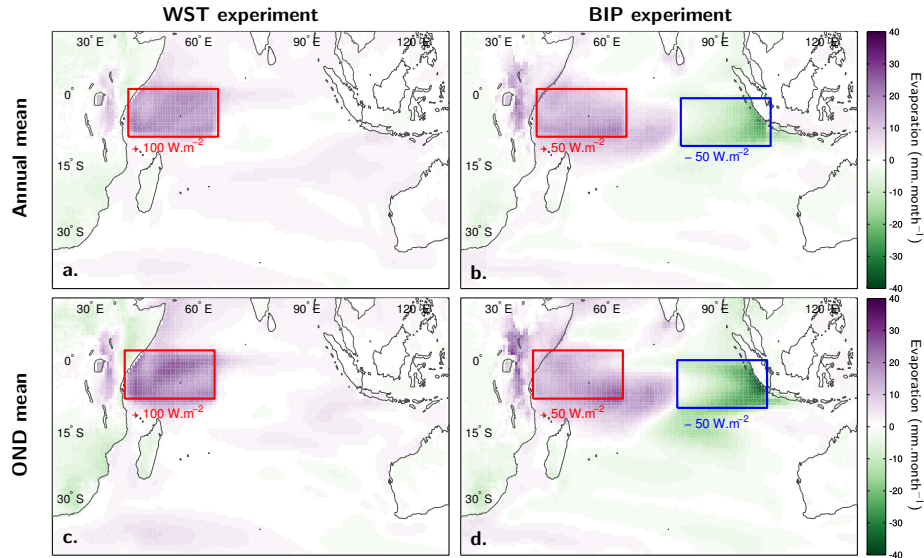


Figure 4.10 – Spatial annual and OND mean evaporation anomalies in mm.month^{-1} in the WST (left panels) and the BIP (right panels) experiments.

In the WST experiment, the enhanced evaporation mostly remains confined in the area where the perturbation is applied, although a thin strip between the lakes Malawi and Turkana is also characterized by positive anomalies. In contrast, in the BIP experiment, the positive anomalies of evaporation are spread over the whole western part of the Indian Ocean, as well as over most of the East African region, including the great Horn of Africa. This increased evaporation over East Africa can be observed during the entire year, but is slightly more pronounced in OND in the BIP experiment.

These different patterns of evaporation anomaly give some insights on the underlying processes. In the WST experiment, most changes in rainfall appear primarily governed by local thermodynamic. Indeed, higher SSTs in the western Indian Ocean induce increased local evaporation and rainfall, which slightly impacts the adjacent regions, including a part of East Africa. Those thermodynamics effects alone cannot explain the much higher and far more widespread positive anomalies of rainfall over East Africa in the BIP experiment, where dynamical phenomena have likely played a role in addition to the local increased convection.

The rainfall increase over East Africa in the BIP experiment is actually caused by low-level easterly anomalies that occur over the whole equatorial Indian Ocean, while weak westerly anomalies are observed in central Africa (Fig. 4.11 right). This is seen with annual mean results, but these wind anomalies are especially pronounced in OND, where a shift in prevailing wind direction is observed: the climatological westerlies are then indeed replaced by easterlies around the equator (not shown). This creates an anomalous convergence zone over the western Indian Ocean and the East African region, associated with ascending motions and enhanced convection.

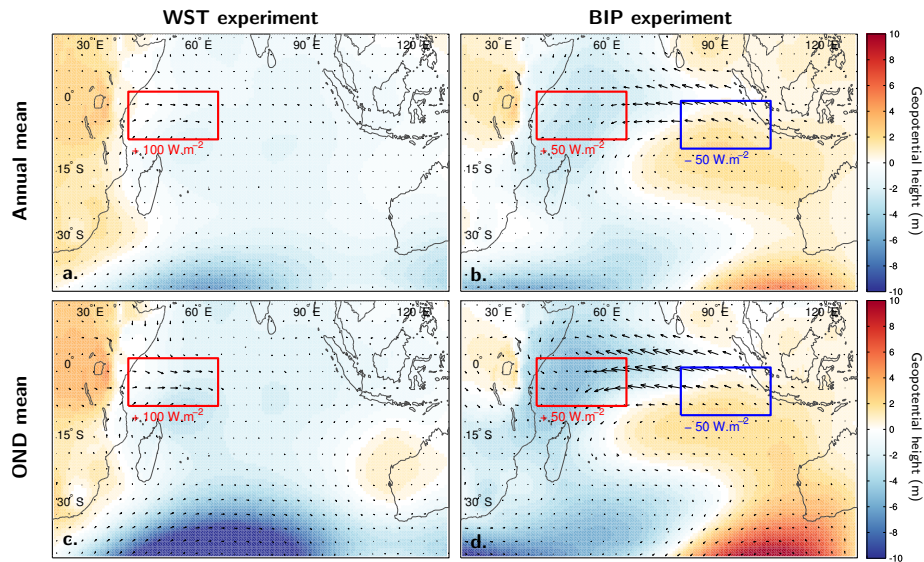


Figure 4.11 – Spatial annual and OND mean geopotential height anomalies and wind anomalies (vectors proportional to the wind speed anomalies) at 850 hPa (in m) in the WST (left panels) and the BIP (right panels) experiments.

The easterly anomalies observed in the BIP experiment are linked to a zonal gradient of pressure over the Indian Ocean. The western part of the basin is indeed dominated by abnormally low geopotential heights at the 850 hPa level, while the eastern Indian Ocean is characterized by positive anomalies (Fig. 4.11 right). The same pattern is observed at the 1000 hPa level (not shown). Although some differences exist, it is persistent all year long, and clearer in OND compared to the other seasons (Fig. 4.11-d). This anomalous

zonal pressure gradient over the equatorial Indian Ocean is not observed in the WST experiment, nor the easterly anomalies (Fig. 4.11 left). Hence, the local warm SST anomalies over the western Indian Ocean are not sufficient to induce significant wind anomalies in EC-EARTH, which contrasts once again with the results of Ummenhofer et al. (2009).

The areas in East Africa characterized by increased rainfall coincide with negative 2-meter air temperature anomalies, in both experiments (Fig. 4.12), consistently with Latif et al. (1999). The latent heat required for the evaporation that is taken out of the surface may play a role in this cooling. However, it is probably mostly due to reduced incoming solar radiation resulting from increased cloud cover associated to enhanced convective activity (Fig. 4.13), as discussed in Ummenhofer et al. (2009).

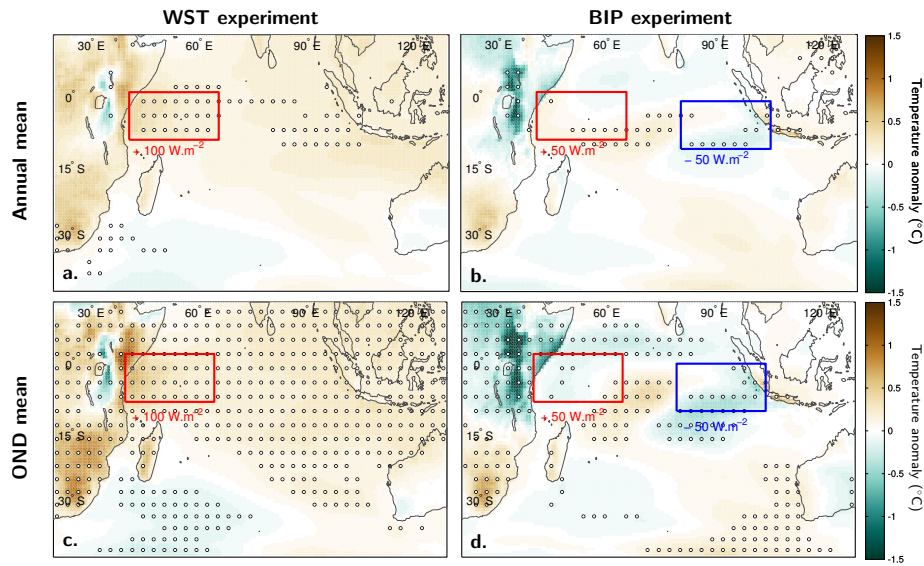


Figure 4.12 – Spatial annual and OND mean 2-meter air temperature anomalies (in °C) in the WST (left panels) and the BIP (right panels) experiments. The null hypothesis of no difference between the sensitivity experiments and the control run can be rejected at the 5% level in areas overprinted with white circles.

Nearly no decrease in 2-meter air temperature is observed over the western part of the Indian Ocean, while this area is also characterized by increased evaporation and cloud cover. Actually, the negative anomalies in latent heat

flux and surface net radiation are not able to offset the constant flux of 50 W.m^{-2} artificially imposed at the surface of the western Indian Ocean in the BIP experiment. In the WST experiment, a relatively slight increase in the 2-meter air temperature is observed homogeneously over the Indian Ocean. However, the relatively modest warming of the air close to the surface in the western Indian Ocean, despite the flux of 100 W.m^{-2} that is applied in the WST experiment, illustrates the large role of the negative feedback initiated by the evaporative cooling and by the clouds, mitigating the warming artificially imposed.

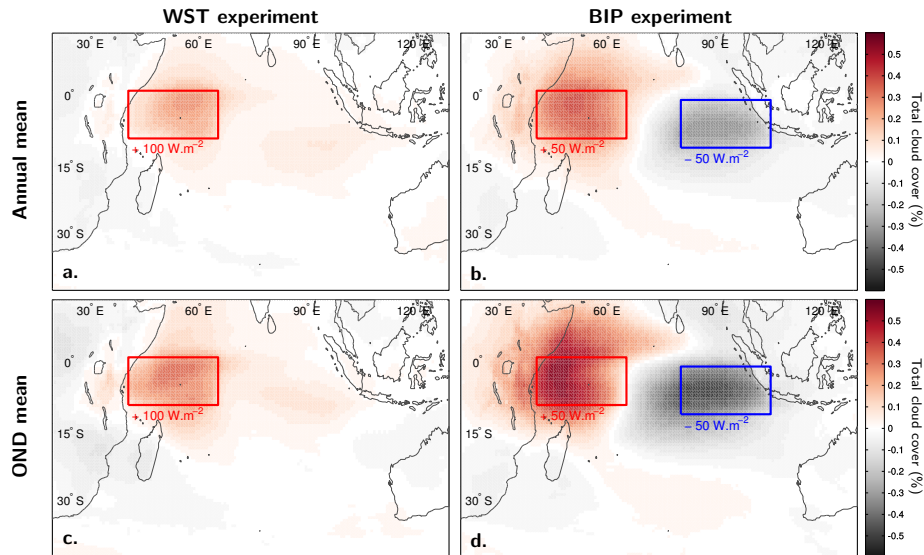


Figure 4.13 – Spatial annual and OND mean cloud cover anomalies (in %) in the WST (left panels) and the BIP (right panels) experiments.

4.5 Summary and conclusions

The goal of this chapter is to assess the mechanisms responsible of the correlation between Indian Ocean SST and the East African rainfall. To do so, the impact of two different spatial distributions of SST anomalies has been estimated. The first pattern considered consists in warmer surface water in the western tropical Indian Ocean. The second one is characterized by an

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enhanced SST gradient between the western and the eastern tropical Indian Ocean, with warmer surface temperature in the west and cooler in the east, reminiscent of a positive phase of the IOD.

The first case leads to increased evaporation and convective rainfall within the area where the SSTs are higher, but also slightly beyond, including some parts of East Africa. The increase in rainfall in East Africa is, however, modest and barely detectable relative to the natural fluctuations. Furthermore, some East African regions, such as the Great Horn, are instead characterized by decrease in rainfall.

The increase in the East African rainfall resulting from the enhanced gradient over the tropical Indian Ocean is much larger and covers the whole of East Africa. It is related to the convergence of winds over the area. Indeed, the SST anomalies over the tropical Indian Ocean induce a gradient of low-level pressure, which drives easterly anomalies over the entire width of the basin, while weak westerly anomalies are present in central Africa. This effect is clearly maximum during the short rains, known to be closely teleconnected to Indian Ocean SSTs.

The role played by the easterly anomalies in the tropical Indian Ocean in the enhancement of rainfall over East Africa has been highlighted in several studies (e.g. Black et al., 2003; Goddard and Graham, 1999; Ummenhofer et al., 2009). However, although observations show that increased East African rainfall often coincides with a SST dipole with warmer surface water in the west and cooler in the east (e.g. Black et al., 2003; Clark et al., 2003), only the western pole is suggested to be of importance to produce the convergent flow in the region in Goddard and Graham (1999) and Ummenhofer et al. (2009). Here, we show that, on the contrary, only the dipole can initiate this circulation pattern change bringing enhanced East African rainfall.

This discrepancy with previous studies can be explained by the use of different models and experimental designs. The model used here, EC-EARTH, simulates quite well the climatological East African rainfall and its link with the Indian Ocean SSTs that are the main driver of its interannual variability. This may partly be explained by its high spatial resolution, reaching about 0.70° in latitude and longitude, as it has been shown that an increased resolution improves the representation of major features of the general circulation such as, among other things, the positioning and seasonal migration of the ITCZ (Gao et al., 2006). This is related to a better representation of the to-

pography, but also to the direct sensitivity of the model physics and dynamics to the resolution (Gao et al., 2006). In comparison, the spatial resolution of the atmosphere models used in the studies of Ummenhofer et al. (2009) and Goddard and Graham (1999) is of about 2.8° .

Another part of the discrepancy between our results and the ones of Goddard and Graham (1999) and Ummenhofer et al. (2009) probably arises from differences in the experimental design. Here, an artificial flux is applied to the western and eastern Indian Ocean SSTs in a fully coupled GCM to generate the anomalies. Goddard and Graham (1999) and Ummenhofer et al. (2009) have used atmosphere models driven by prescribed SSTs derived from observations. While this allows them to better control the pattern and the magnitude of the SST anomalies, they cannot take into account the impact of the atmosphere on the SSTs, and they can potentially impose to the atmosphere a pattern that is not consistent with the physics of the atmosphere models used.

Assessing the robustness of the results obtained here and the impact of the model selected and of the experimental design of the experiment would require additional sensitivity experiments with EC-EARTH, using the same experiments design as in Ummenhofer et al. (2009), and to repeat the same analysis with other climate models. While this is out of the scope of this chapter, this is clearly an interesting perspective of the study. This discussion illustrates that it is not possible yet to obtain robust conclusion from the available experiments as the results of a study focusing on the East African rainfall using the results of one single model are likely very dependent of the behaviour of the particular model selected. Such studies must thus be considered with caution.

CHAPTER 5

CONCLUSIONS

THE overarching scientific question of this thesis is “How the East African rainfall is linked to the Indian Ocean SSTs at the interannual to the multi-decadal time scale?”. It has been answered in the different chapters using various complementary methodologies. This section summarizes the main outcomes of the thesis through the development of the three main points presented in the general introduction.

5.1 Improving understanding of the link between East African rainfall and Indian Ocean SSTs and of the underlying mechanisms

The interannual variability of the East African rainfall is mainly controlled by the short rains, that are strongly correlated with the Indian Ocean SSTs. Observations show that increased East African rainfall often coincides with a dipole in the tropical Indian Ocean SSTs, with anomalous cold surface water in the eastern tropical Indian Ocean and anomalous warm water in the western

part of the basin, a pattern reminiscent of a positive phase of the Indian Ocean dipole.

However, before mentioning the main findings relative to this relationship between the East African rainfall and Indian Ocean SSTs, it is important to stress that the whole East African region, as defined in the general introduction, is not characterized by the same link with the Indian Ocean. This heterogeneity has actually been emphasized in each chapter of this work. In Chapter 2, we have shown that the correlation coefficients between rainfall averaged over the equatorial East Africa and the Indian Ocean SSTs are high, while they are very low and non-statistically significant when considering rainfall averaged over the southeastern, but still inter-tropical, East Africa. Also, the heterogeneity of those two East African sub-regions regarding their link with Indian SSTs has also been highlighted in Chapter 3, using a data assimilation method with the GCM CESM1. Indeed, we have shown in this chapter that precipitation over southeastern inter-tropical East Africa is very isolated from the large-scale SSTs, unlike rainfall over the equatorial East African region. In the same vein, the impact of different imposed patterns of SSTs anomalies in the Indian Ocean on the East African rainfall is clearly not homogeneous over the region, as illustrated in Chapter 4 based on sensitivity experiments using the GCM EC-EARTH.

Where the link between rainfall and Indian Ocean SSTs is strong, as for instance in equatorial East Africa, the last millennium simulations performed by several GCMs suggest that the teleconnection is controlled at the interannual time scale by internal variability, the impact of external forcings being negligible. However, the role played by the forcings on this link increases when considering lower frequency variability. Indeed, the dipole pattern in the Indian Ocean is still present in the time series smoothed to highlight decadal to centennial variations, but only in fixed-forcing simulations. If the last millennium forcings are taken into account, the East African rainfall are no more associated with a dipole in the Indian Ocean but rather by a monopole, with relatively homogeneous positive correlations between rainfall and SSTs over the whole basin.

In Chapter 4, sensitivity analyses performed with the GCM EC-EARTH allow studying the processes involved in the statistical link between the East African rainfall and Indian SSTs. We have shown that both poles of the Indian Ocean dipole – warmer surface water in the west and cooler in the east

– are crucial to drive enhanced East African rainfall, while only the western Indian Ocean warmer surface water was suggested to be of importance in previous studies (e.g. Goddard and Graham, 1999; Ummenhofer et al., 2009). Yet the processes involved are roughly similar as suggested earlier. The anomalous pattern of SST leads to an alteration of the atmospheric circulation, with enhanced low-level easterly anomalies over the tropical Indian Ocean. Equatorial central and eastern Africa being characterized by weak westerly anomalies, these winds converge over the western Indian Ocean and the East African region. This is associated with ascending motion and increased convective activity over the region leading to enhanced precipitation. These changes are maximum in boreal autumn, during the East African short rains. In our experimental setup, this reorganisation of the atmospheric circulation cannot be driven only with increased SSTs over the western Indian Ocean, which thus contrasts with previous similar model-based studies. This illustrates the wide range of behaviour of the climate models regarding their representation of the East African hydroclimate and the related physical processes, as explained in the following section.

5.2 Assessing the ability of the state-of-the-art GCMs in simulating the link between the East African rainfall and Indian SSTs, and the East African hydroclimate variations over the last millennium

The results mentioned above relies on the capability of the GCMs to simulate realistically the East African hydroclimate and its link to the large scale SSTs. As seen in Chapter 2, climate models generally struggle to reproduce well these features. The climatological unimodal seasonal cycle of rainfall observed in the southeastern inter-tropical Africa is in general relatively well simulated, but the bimodal seasonality characterizing the equatorial East Africa is less well captured, with a systematic underestimation of the long rains and overestimation of the short rains.

Comparing model results and available proxy-based reconstructions of hydroclimate over the last millennium could be of great interest to place the current East African hydroclimate trends in a broader context. However, we

suggest in Chapter 2 that the simulated changes over the last millennium are mostly driven by internal variability rather than by external forcings. Indeed, the variances of the simulated hydroclimate are very similar in fixed and time-varying forcing experiments for the GCMs used, and no common hydroclimate changes are found throughout the last millennium among models, while they are driven by comparable forcings. This obviates the possibility of general agreement between the time series of model results and proxy-based reconstructions, and makes this model-data comparison exercise meaningless. Note that, however, some GCMs show a response to the forcings after 1850, but this response is not consistent among these models.

In this context, the assessment of the climate model performance in simulating the right timing of the past millennium wet or dry events relative to reconstructions or observations cannot be achieved. However, the realism of their mean pattern of correlations between East African rainfall and Indian Ocean SSTs can be assessed. We have shown in Chapter 2 that most GCMs do not represent the observed relationship between the East African rainfall and Indian and Pacific SSTs over the recent past, while its importance to drive the interannual variability of the East African rainfall is well established. Nevertheless, CESM1, EC-EARTH and, to a lesser extent, MPI-ESM-P, simulate realistic patterns of correlations. Together with the availability of a last millennium ensemble of ten simulations, the relatively good performance of CESM1 relative to recent observations is the reason why this model is deemed a particularly suitable GCM to study whether the observed covariance between the East African rainfall and Indian Ocean SSTs can be used to improve the reconstructions of both variables, which is described in the next point.

5.3 Investigating the potential interest of using the link between the East African rainfall and Indian SSTs to obtain better reconstructions of both variables during the last millennium

Using the covariance observed between Indian Ocean SSTs and the East African rainfall through a method of data assimilation allows obtaining improved reconstructions of both variables over the last millennium, as shown in

Chapter 3. However, this is true only when considering an ideal framework, when assimilating pseudo-proxy data deduced from the same model than the one that has provided the ensemble of simulations, ie. here CESM1. With a more realistic -but still simplified- framework, two limitations lead to a strong deterioration of the reconstructions skill. First, considering biases in model physics by assimilating pseudo-proxies derived from other GCMs or from instrumental data sets prevents obtaining skillful reconstructions of one variable based on the assimilation of the other. Furthermore, when assimilating the East African rainfall, the information is no more spatially spread, which results in the improvement of only local precipitation. In contrast, the whole Indian Ocean SST can still be reconstructed only based on the assimilation of the information contained in a few grid cells spread over the Ocean.

The assimilation of real proxy-based reconstructions brings new issues that make the data assimilation process more complex. First, the variable reconstructed from proxy record is often not explicitly simulated in the climate model, while the data assimilation involves a direct comparison between the variables derived from the two sources. Second, the uncertainty of the data has to be taken into account, but is sometimes hard to define. In Chapter 3, besides the use of a forward model to estimate the model version of the proxy record time series, a local calibration had to be applied to each proxy-based reconstruction assimilated to take into account the differences in the link between simulated variables and proxy depending on the location. This allows obtaining skillful reconstructions of the Indian Ocean SSTs based on the assimilation of the $\delta^{18}\text{O}$ content of six coral archives spread over the Indian Ocean.

5.4 General conclusion

In all the analyses achieved in this work, we were confronted with the difficulties met by the climate models to simulate the East African hydroclimate and its link to the Indian Ocean SSTs. In this regard, one of the key message here is that one should be extremely careful when interpreting the model results over East Africa. Although all diagnostics performed here are model-dependent, we are convinced that the climate models are essential tools to establish the plausible causes for hydroclimate variations in the region, especially over periods when observations are scarce or non-existent.

However, before using the models, they should be carefully tested against available observations to make sure they fit as much as possible the needs required for the analyses performed. Also, the robustness of the results obtained using one climate model should be validated by replicating the same analyses using other climate models. On the other hand, using multi-model mean results should be avoided. In our case, it would only mask the wide range of variations observed among models regarding the East African hydroclimate over the last millennium and the teleconnections between the East African rainfall and the Indian ocean SSTs. In this context, the initiatives allowing integrating the empirical information from observations or proxy-based reconstruction into climate models, such as data assimilation, are of great interest to improve the reliability of the simulated changes, as for instance demonstrated in Klein et al. (2014). In this case, however, a particular attention has to be given to the uncertainties of these data, and to their inclusion in the data assimilation process.

Given the above information, some further work could certainly be useful to refine and to go beyond the results obtained in this thesis, as presented in the next section.

5.5 Perspectives

A logical follow-up to this study would be to replicate the analyses achieved in Chapter 4 using other GCMs to assess the robustness of our findings, and the sensitivity of the results to the experimental design. Identifying the right pattern of Indian Ocean SST anomalies and the underlying processes that actually influence the variability of the East African rainfall is crucial to improve forecasts of the incoming extreme events. Yet the results found here are not consistent with previous published studies, showing the interest to systematically repeat such analyses using the same experimental design but different climate models.

We have seen in Chapter 2 and 3 how useful the ensemble of simulations performed by the model CESM1 is. It has allowed, among other things, distinguishing the internal to the forced variability and performing data assimilation analyses. Yet, to our knowledge, only two last millennium ensembles of simulations performed with GCM exist: the one performed with the model MPI-

ESM (Jungclaus et al., 2010) and the one we have used, which is the largest with ten simulations. Making available newly-performed ensemble of simulations using other GCMs would help assessing the robustness of the conclusions of Chapter 2 and 3.

Data assimilation requires a direct comparison between the reconstructed and the simulated variable. However, the empirical information derived from proxy records are often not included explicitly in climate models. The difficulties met when comparing these variables in Chapter 3 show the importance to continue the ongoing effort to reconcile the variables from both sources of information, through forward modelling for instance.

The analyses performed in this study have not specifically addressed the changes in extreme meteorological events. We have underlined and characterized the link between the East African rainfall and the Indian Ocean surface water at different time scales, analysing the full time series. An interesting perspective would be to repeat the same kind of analyses but focusing on the extremes events, by only selecting the abnormally wet or dry years, and to investigate whether a specific oceanic dynamics is associated to those extreme events.

A more general - and complicated - perspective would be to identify the causes behind the wide range of performance characterizing the GCMs in simulating the East African rainfall and its link with the Indian Ocean. Why some models perform relatively well while others don't? This question is very broad, given the multiple physical but also technical potential origins of the discrepancy. The resolution of the different models likely plays a role, often too coarse to represent small-scale processes such as the convection and cloud processes, which forces the models to use quite uncertain parameterizations. Furthermore, the spatial resolution also has a strong influence on larger-scale circulation features such as the positioning and seasonal migration of the ITCZ, which is directly linked to the East African rainfall. Answering this question would require multiple sensitivity experiments, while producing new experiments with GCMs is very demanding in terms of computer resources. Yet the precise identification of the limitations of climate models as illustrated here could serve as the basis for improving the dynamics of these models, whose limitations have to be kept in mind when interpreting the results of this thesis.



SUPPLEMENT TO CHAPTER 2

A.1 Supplementary figures

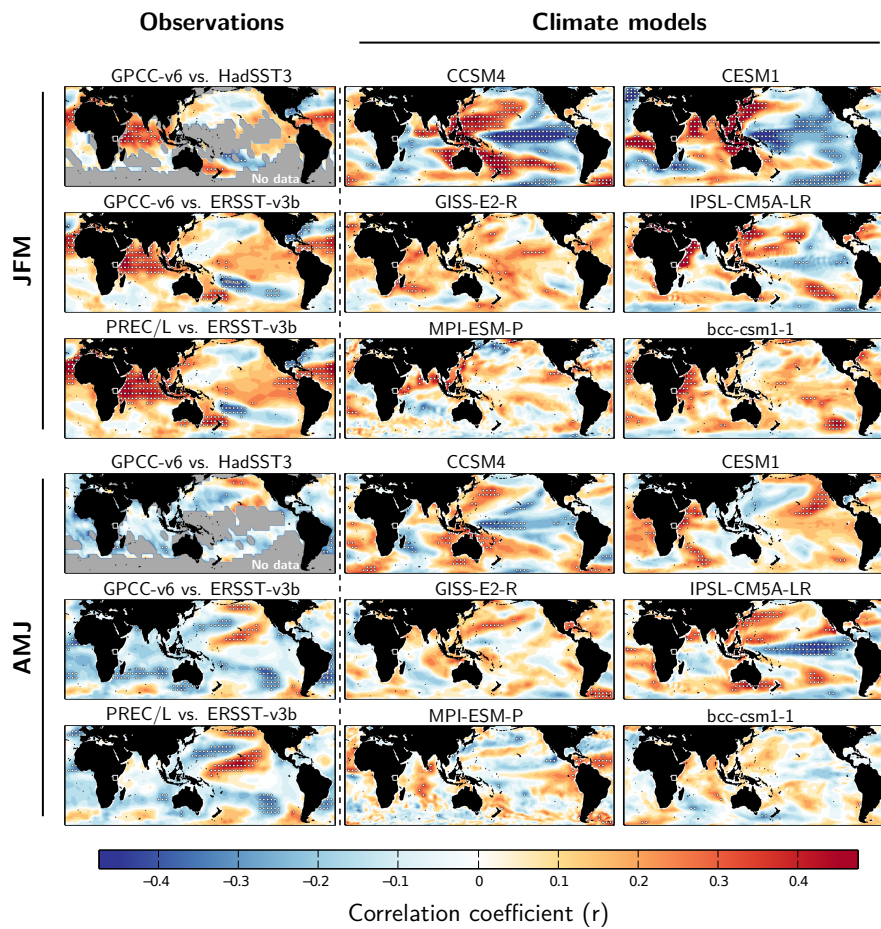


Figure A1 – Pearson correlation coefficients between mean JFM and AMJ rainfall over the Challa/Naivasha region and global SSTs in observations and climate models (here, only the first member `r1i1p1` is used) for the period 1950-2000. In areas over-printed with white circles, a null hypothesis of no correlation can be rejected at the 5% level. No data are available from grey areas.

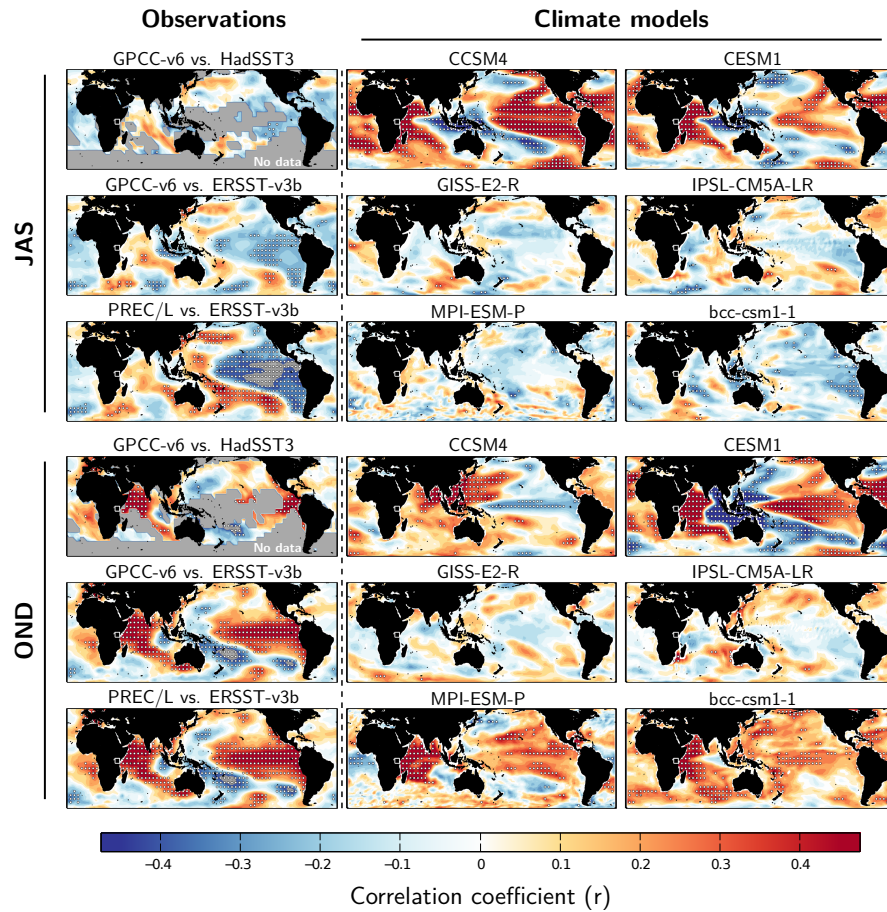


Figure A2 – Same as in Fig. A1 but for the results averaged over the months JAS and OND.

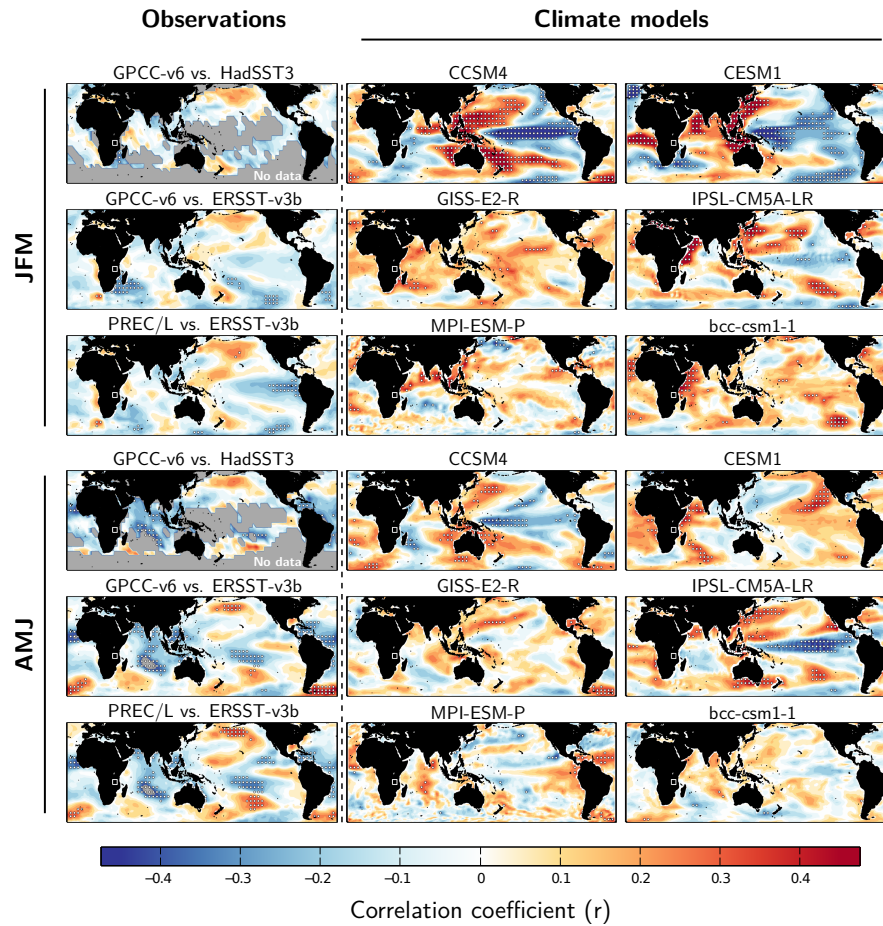


Figure A3 – Pearson correlation coefficients between mean JFM and AMJ rainfall over the Masoko/Malawi region and global SSTs in observations and climate models (here, only the first member r1i1p1 is used) for the period 1950-2000. In areas over-printed with white circles, a null hypothesis of no correlation can be rejected at the 5% level. No data are available from grey areas.

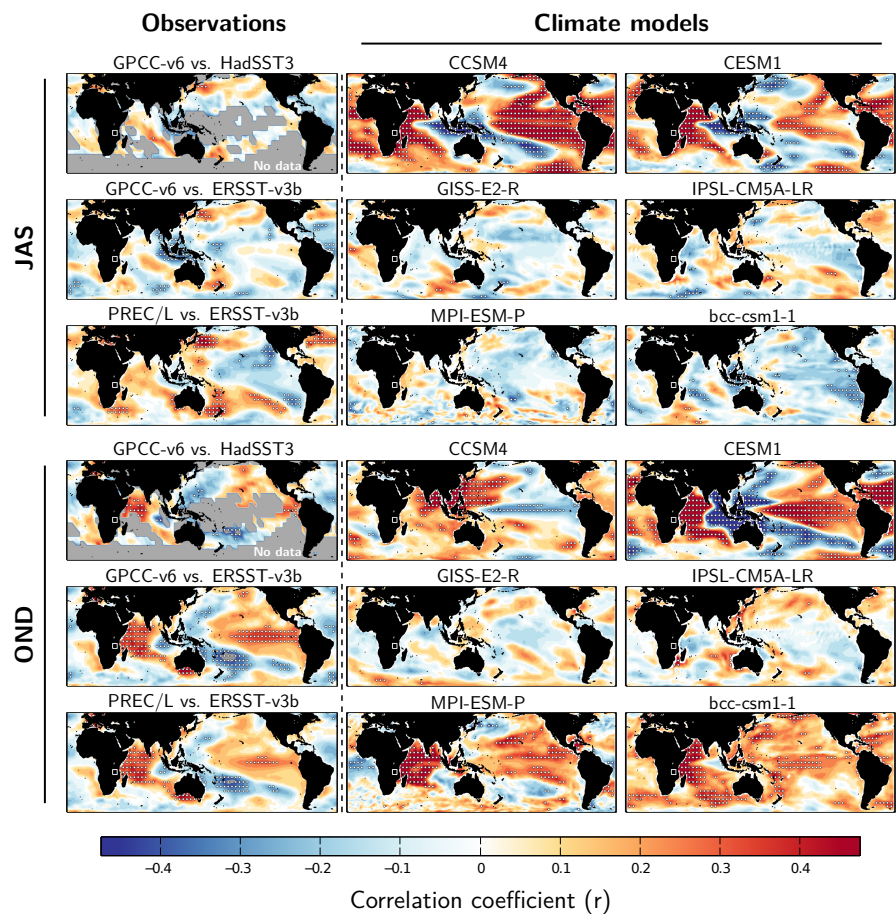


Figure A4 – Same as in Fig. A3 but for the results averaged over the months JAS and OND.

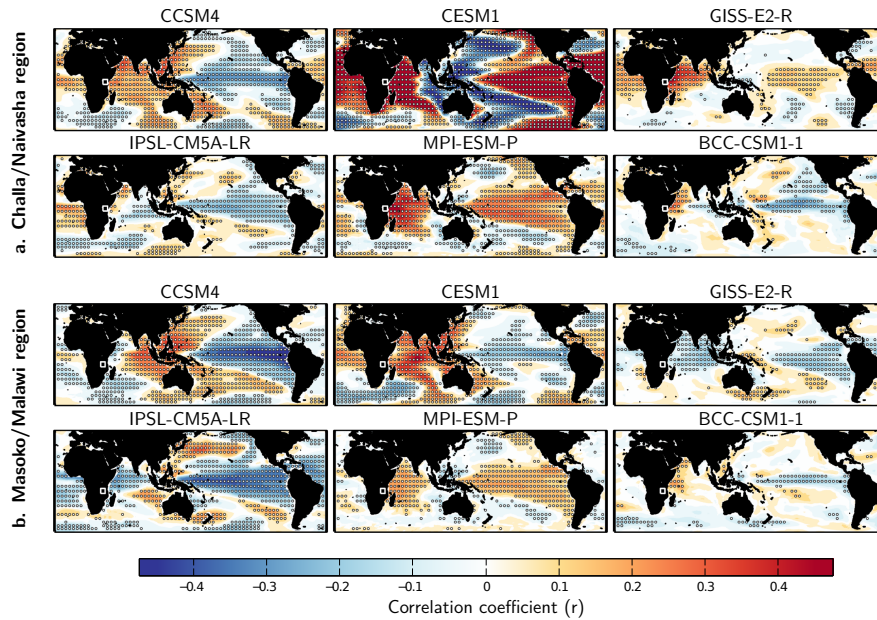


Figure A5 – Pearson correlation coefficients between mean annual rainfall over the Challa/Naivasha region (a, upper two rows) or Masoko/Malawi region (b, lower two rows) and global SSTs in the *pre-industrial control* runs of the climate models. In areas overprinted with white circles, a null hypothesis of no correlation can be rejected at the 5% level. No data are available from grey areas.

A.2 Supplementary tables

Table A1 – Information about proxy-based reconstructions used in this study.

Site	Proxy type	Reconstructed variable	Period (yrs AD)	Mean temporal resolution (yrs)	Age model derived from	reference
Challa	Branched and isoprenoidal index (BIT)	Runoff	-22972–1980	124	^{14}C and ^{210}Pb	Verschuren et al. (2009)
Challa	$\delta\text{D}_{\text{wax}}$	Isotopic composition of rainfall	-22972–1980	180	^{14}C and ^{210}Pb	Tierney et al. (2011)
Challa	Varve thickness	Wind and rain-driven changes in lake biology	-1050–2005	1	Varve counts	Wolff et al. (2011)
Naivasha	sediment stratigraphy, species compositions of fossil diatom and midge assemblages	Lake level	884–1993, 6	3	^{14}C , ^{210}Pb and fossil evidence	(Verschuren et al., 2000)
Masoko	Low-field magnetic susceptibility	Wind-stress and/or lake-level amplitude changes	-43308–2001	25	^{14}C	Garcin et al. (2006)
Masoko	Low-field magnetic susceptibility	Wind-stress and/or lake-level amplitude changes	1511–2002	5	^{14}C , cross-core correlation, tephra	Garcin et al. (2007)
Malawi	Terrigenous mass accumulation rate (MAR)	Runoff	1270–1978	6	^{210}Pb and varves counts	Brown and Johnson (2005); Johnson and McCave (2008)

Table A2 – Pearson correlation coefficients between observed and simulated rainfall-SSTs correlation maps for the Challa/Naivasha region (Fig. 2.6a.) and the Masoko/Malawi region (Fig. 2.6b.), for annual mean results and October-November-December (OND) mean results.

	Challa-Naivasha		Masoko-Malawi	
	annual	OND	annual	OND
CCSM4	-0.36*	-0.30*	0.07*	-0.26*
CESM1	0.27*	0.61*	-0.01	0.51*
GISS-E2-R	-0.01	-0.18*	0.24*	-0.16*
IPSL-CM5A-LR	-0.10*	-0.08*	0.10*	0.08*
MPI-ESM-P	0.16*	0.39*	0.15*	0.43*
BCC-CSM1-1	0.00	0.17*	0.05*	0.12*

* significant at the 5% level

Table A3 – Pearson correlation coefficients between simulated and reconstructed hydroclimate time series. Model results over the region Challa/Naivasha (Masoko/Malawi) are compared to proxy-based reconstruction of Challa (Masoko), Naivasha (Malawi), and the mean between the two. The coefficients are computed over the periods covered by the data at annual resolution. Model time series are filtered using a loess method with a window of 100 years. The autocorrelation introduced in the model and reconstructions curves in response, respectively, to the smoothing and to the interpolation is taken into account when assessing the significance of the correlations (t-Test).

Variable: P-E	Challa	Naivasha	Challa/ Naivasha	Masoko	Malawi	Masoko/ Malawi
CCSM4	-0.03	0.22	-0.01	-0.03	0.12	-0.00
CESM1	-0.07	-0.16	-0.26	0.33	0.15	0.43*
GISS-E2-R	0.08	0.35	0.38*	-0.02	0.10	0.14
IPSL-CM5A-LR	0.01	-0.03	0.01	0.02	0.01	0.18
MPI-ESM-P	-0.05	-0.22	-0.23	-0.11	-0.13	-0.13
BCC-CSM1-1	0.26	-0.10	0.03	-0.28	-0.01	-0.03

* significant at the 5% level

A.3 Supplementary discussion

Supplementary discussion: comparison between reconstructions and the integration of simulated P-E

To address the issue concerning the memory mismatch between the simulated and the reconstructed hydroclimate variables, we have used a first order

autoregressive model (AR-1) model driven by the simulated P-E time series, which introduces some memory in the system depending on the parameter α (Eq. A.1):

$$X(t+1) = \alpha X(t) + (P-E)(t) \quad (\text{A.1})$$

where X is the emulated system and α the autocorrelation parameter. Note that to be represented by an autoregressive model, the process has to be stochastic. Although P-E is not fully stochastic, it can be considered as not far to so this is not a strong violation of the assumption. All four sites have time scales of variability from a few decades to a century. We have thus chosen a similar α equal to 0.98, which means that 2% of the signal will be lost each year. We also have done the test with an α of 1, which represents the integration of the time series through the whole period. This is equivalent to the estimation of the level of a bucket with no runoff which is increasing if P-E is positive and decreasing if it is negative. This is an extreme case, since the long-term impact of any perturbation will be overestimated, but this provides useful upper bound to test the influence of the memory of the lake on model-data comparison. The AR-1 model with an α of 0.98 (Fig. A6) and the full integration of P-E (Fig. A7) emphasizes the low-frequency changes that lead time series to appear more similar to reconstructions.

Although the absolute values of the correlation coefficients are generally higher, especially for the integrated time series (Tables A4 and A5), the model-data agreement is not substantially improved. Most models do not simulate any reconstructed time series, and the ones that show some skills at simulating reconstructed hydroclimate in one region perform badly in the other region. This is because, although they show different curves in Masoko/Malawi and in Challa/Naivasha they are unable to simulate the dipole between these regions as observed in reconstructions between 1400 to around 1800.

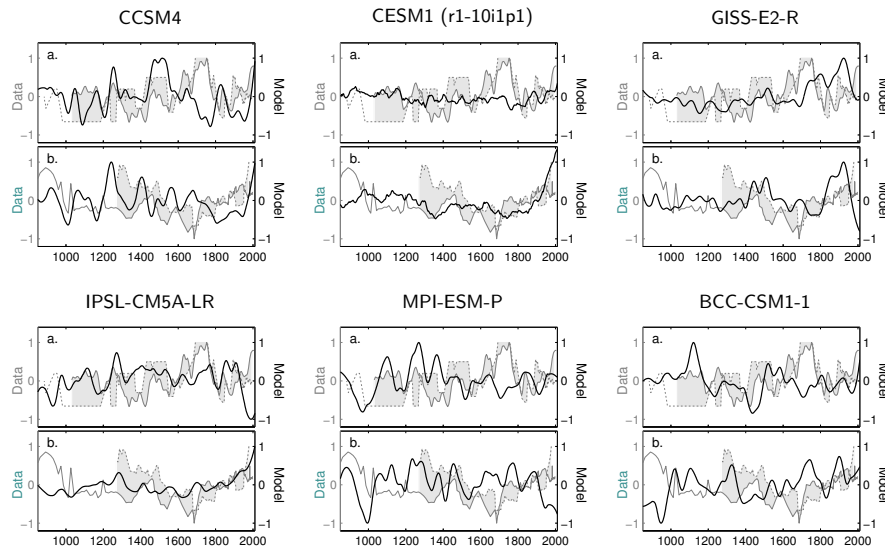


Figure A6 – Comparison between last-millennium time series of the reconstructions (in grey) and of the AR1 model applied to P-E simulated by six GCMs (in black, using an α equal to 0.98) averaged over the Challa/Naivasha region (a), with the Naivasha record shown as dashed line and the Challa record as solid line; and over the Masoko/Malawi region (b), with the Malawi record shown as dashed line and the Masoko record as solid line. In both regions, the area between the two records is shaded in light grey. Both proxy-based and simulated time series are presented as anomalies with respect to the whole period, and are linearly standardized so that the absolute maximum equals 1. Ordinate axes are oriented such that wetter (drier) conditions point upwards (downwards). Model time series are annual mean values filtered using a loess method with a window of 100 years. For the CESM1 model, the black curve is the median of the ten ensemble members previously standardized and smoothed.

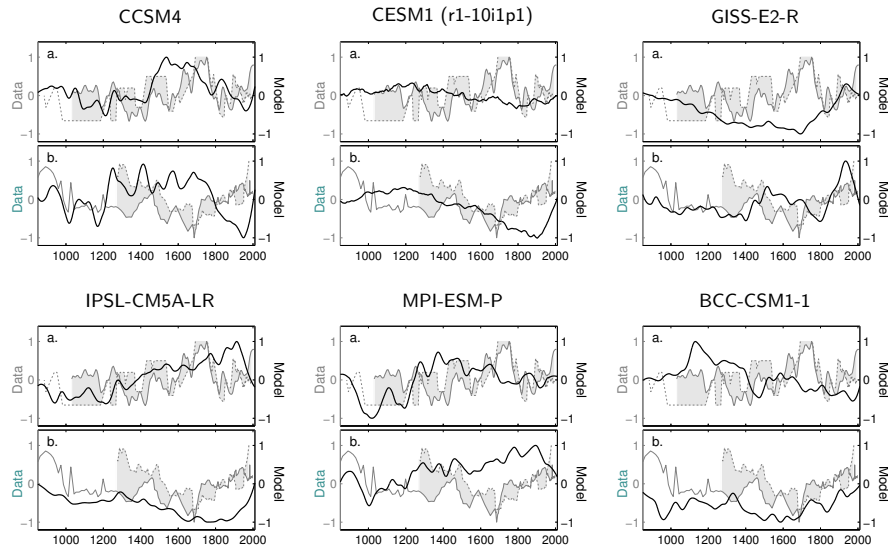


Figure A7 – Same as in Fig. A6, but using the integration over the whole period of simulated P-E of models (AR1 model with an α of 1).

Table A4 – Same as in Table A3, but using the AR1 model applied to the simulated time series of P-E in models, with α equal to 0.98.

Variable: P-E	Challa	Naivasha	Challa/ Naivasha	Masoko	Malawi	Masoko/ Malawi
CCSM4	-0.17	0.18	-0.12	-0.06	0.13	-0.13
CESM1	0.08	-0.37*	-0.24	0.29	0.29	0.43*
GISS-E2-R	0.05	0.33	0.27	0.11	0.11	0.31
IPSL-CM5A-LR	-0.18	0.14	0.08	0.11	0.30	0.52*
MPI-ESM-P	-0.14	-0.13	-0.38	-0.10	-0.04	-0.11
BCC-CSM1-1	0.07	-0.43*	-0.28	-0.32	-0.20	-0.06

* significant at the 5% level

Table A5 – Same as in Table A3, but using the integration of simulated P-E in models over the whole period.

Variable: P-E	Challa	Naivasha	Challa/ Naivasha	Masoko	Malawi	Masoko/ Malawi
CCSM4	0.23	0.33	0.39*	-0.33	-0.10	-0.42
CESM1	-0.28	-0.35	-0.46*	-0.08	0.56*	0.14*
GISS-E2-R	0.02	-0.33	-0.28	0.22	-0.15	0.06
IPSL-CM5A-LR	0.14	0.52*	0.47*	0.42*	0.81*	0.60*
MPI-ESM-P	-0.18	0.56*	0.19	-0.06	-0.27	0.04
BCC-CSM1-1	-0.23	-0.54*	-0.52*	0.43*	0.30	0.55*

* significant at the 5% level



SUPPLEMENT TO CHAPTER 3

B.1 Supplementary figures

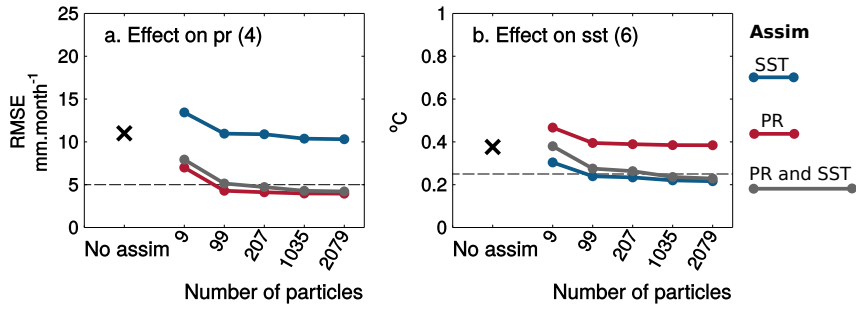


Figure B1 – RMSE between rainfall (a) and SSTs (b) from MPI-ESM-P (pseudo-proxy assimilated) and from the CESM-LME without data assimilation (black cross, ensemble mean) and with data assimilation considering different number of particles (dots, weighted mean of the ensemble). The experiments assimilating only the four East African rainfall results are shown in blue, the experiments that only consider the assimilation of the six Indian SST results are shown in red, and the experiments with the assimilation of both variables in grey. The horizontal black lines represent the data error.

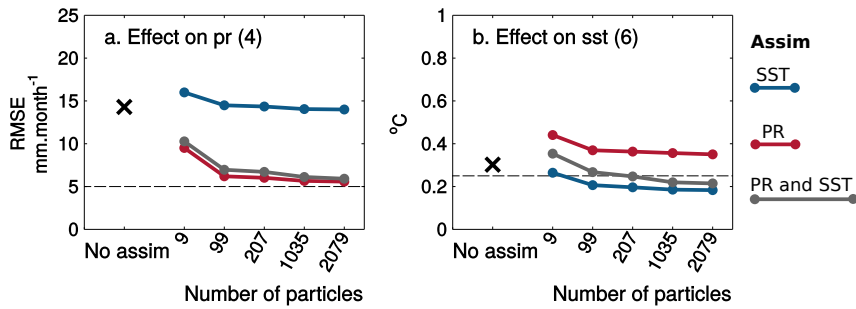


Figure B2 – RMSE between rainfall (a) and SSTs (b) from GISS-E2-R (pseudo-proxy assimilated) and from the CESM-LME without data assimilation (black cross, ensemble mean) and with data assimilation considering different number of particles (dots, weighted mean of the ensemble). The experiments assimilating only the four East African rainfall results are shown in blue, the experiments that only consider the assimilation of the six Indian SST results are shown in red, and the experiments with the assimilation of both variables in grey. The horizontal black lines represent the data error.

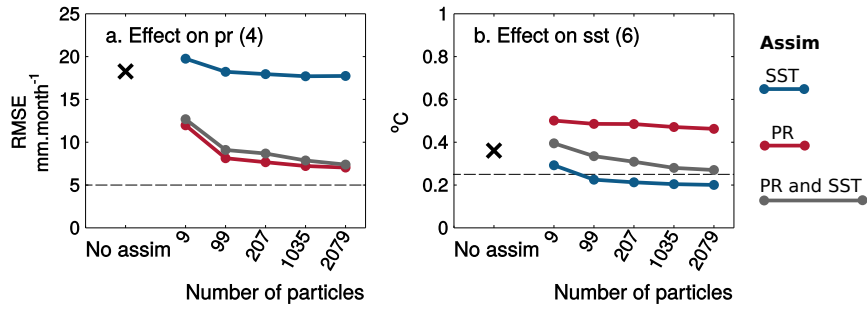


Figure B3 – RMSE between rainfall (a) and SSTs (b) from the assimilated observation data sets (GPCC-v7 for rainfall and ERSST-v4 for SSTs) and from the CESM-LME without data assimilation (black cross, ensemble mean) and with data assimilation considering different number of particles (dots, weighted mean of the ensemble). The experiments assimilating only the four East African rainfall results are shown in blue, the experiments that only consider the assimilation of the six Indian SST results are shown in red, and the experiments with the assimilation of both variables in grey. The horizontal black lines represent the data error.

B.2 Study of the distribution over time of the particles selected in the experiments with data assimilation of pseudo-proxies derived from MPI-ESM-P and GISS-E2-R

The assimilation of the time series of MPI-ESM-P and of GISS-E2-R shows very similar results regarding the distribution of the calendar years for the particles selected (Fig. B4). As in the case with CESM1, the particles selected are very homogeneously distributed over time in the experiments with the assimilation of rainfall only (not shown), which means that if there is a forced variability driving the precipitations, it is much weaker than the internal variability. By contrast, when assimilating SSTs only, the effect of forcing is even stronger than in the case of the assimilation of the tenth ensemble member of CESM1. The actual years of simulation tend to be more represented (the diagonal line is marked), and the effect of volcanic activity is clearly evidenced. However, instead of choosing the actual volcanic eruptions, only the episodes around 1250 and, to a lesser extent, around 1810 are selected by the particle filter to represent all last millennium volcanic eruptions. The last century warm-

ing is also well visible in both cases, with a darker patch closely surrounding the diagonal at the end of the experiments. This warmer period is, however, sometimes confused with other warm periods over the last millennium, such as the one around 1200-1250. Once again, the combined effect of assimilating both rainfall and SSTs results gives a very noisy picture (not shown).

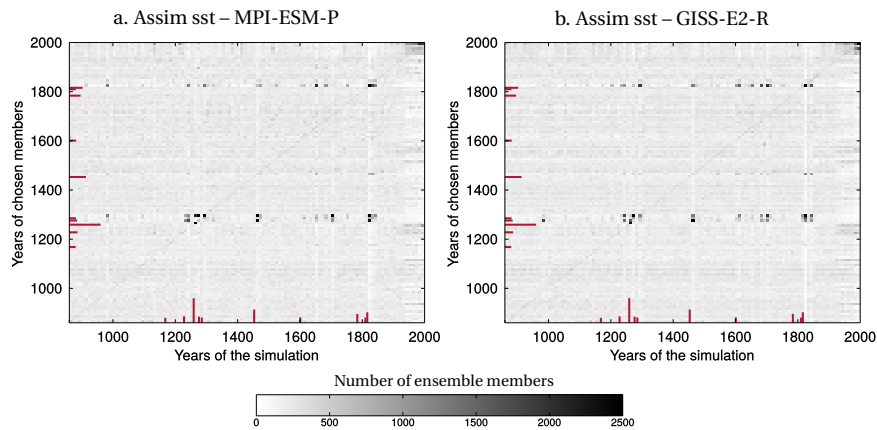


Figure B4 – Years of the particles selected in the data-assimilated model output versus reconstructed years, in the experiments with data assimilation of SSTs from MPI-ESM-P (a) and from GISS-E2-R (b), using 2079 particles. The years are grouped by periods of ten years for a better readability. The red bars are the ten largest volcanic eruptions of the last millennium, with length proportional to the amount of sulphate aerosol released, based on Gao et al. (2008).



PUBLICATIONS AND COMMUNICATIONS RELATED TO THE THESIS

Peer-reviewed articles

- Klein, F. and Goosse, H. (2016). Reconstructing East African rainfall and Indian Ocean sea surface temperatures over the last centuries using data assimilation. Submitted to *Climate Dynamics*.
- Klein, F., Goosse, H., Graham, N. E. and Verschuren, D. (2016). Comparison of simulated and reconstructed variations in East African hydroclimate over the last millennium. *Climate of the Past*, 10(7), 1499-1518.
- Klein, F., Goosse, H., Mairesse, A. and de Vernal, A. (2013). Model-data comparison and data assimilation of mid-Holocene Arctic sea-ice concentration. *Climate of the Past*, 10(3), 1145-1163.

Oral communications

- Klein, F., Goosse, H., Graham, N. E. and Verschuren, D. (Jan. 2016). Comparison of Simulated and Reconstructed Variations in East African Hydroclimate over the Last Millennium. AMS Annual Meeting (New Orleans, USA).
- Klein, F., Goosse, H., Graham, N. E. and Verschuren, D. (Feb. 2015). Comparing East African climate model results with lake records over the last 1000 years. AfQUA Conference (Cape Town, South Africa).
- Klein, F., Goosse, H., Mairesse, A. and de Vernal, A. (Apr. 2014). Model-data comparison and data assimilation of mid-Holocene Arctic sea-ice concentration. EGU General Assembly (Vienna, Austria).
- Klein F. (Nov. 2013). The effect of data assimilation on the simulated mid-Holocene Arctic sea-ice concentration. UCL TECLIM seminars (Louvain-La-Neuve, Belgium).

Poster presentation

- Klein, F., Goosse, H., Mairesse, A., de Vernal, A. and Seidenkrantz, M.-S. (Aug. 2015). Data assimilation of mid-Holocene Arctic sea ice concentration. INQUA Congress (Nagoya, Japan). *Poster presented by H. Goosse*
- Klein, F., Goosse, H., Graham, N. E. and Verschuren, D. (Dec. 2014). Assessing the performance of climate models in East Africa over the last millennium. Young Researchers Overseas' Day (Brussels, Belgium).
- Klein, F., Goosse, H. and Graham, N. E. (May. 2014). East African climate dynamics over the past millennium in PMIP3/CMIP5 simulations. Third PMIP3 Workshop (Namur, Belgium).
- Klein, F., Goosse, H. and Graham, N. E. (Apr. 2014). East African climate dynamics over the past millennium in PMIP3/CMIP5 simulations. EGU General Assembly (Vienna, Austria).

- Klein, F., Goosse, H., Mairesse, A. and de Vernal, A. (Sept. 2013). The effect of data assimilation on the mid-Holocene modelled sea-ice cover. 12th International NCCR Climate Summer School (Grindewald, Switzerland).

REFERENCES

- Abram, N. J., Gagan, M. K., Cole, J. E., Hantoro, W. S., and Mudelsee, M.: Recent intensification of tropical climate variability in the Indian Ocean, *Nature Geoscience*, 1, 849–853, doi:10.1038/ngeo357, 2008.
- Alexander, M. A., Bladé, I., Newman, M., Lanzante, J. R., Lau, N. C., and Scott, J. D.: The atmospheric bridge: The influence of ENSO teleconnections on air-sea interaction over the global oceans, *Journal of Climate*, 15, 2205–2231, doi:10.1175/1520-0442(2002)015<2205:TABTIO>2.0.CO;2, 2002.
- Amante, C. and Eakins, B. W.: ETOPO1 1 Arc-Minute Global Relief Model: Procedures, Data Sources and Analysis., Tech. rep., NOAA Technical Memorandum NESDIS NGDC-24, National Geophysical Data Center, NOAA, doi:10.7289/V5C8276M, 2009.
- Anchukaitis, K. J. and Tierney, J. E.: Identifying coherent spatiotemporal modes in time-uncertain proxy paleoclimate records, *Climate Dynamics*, 41, 1291–1306, doi:10.1007/s00382-012-1483-0, URL <http://www.springerlink.com/index/10.1007/s00382-012-1483-0>, 2013.
- Annan, J. D. and Hargreaves, J. C.: Identification of climatic state with limited proxy data, *Climate of the Past*, 8, 1141–1151, doi:10.5194/cp-8-1141-2012, 2012.
- Anyah, R. O. and Qiu, W.: Characteristic 20th and 21st century precipitation and temperature patterns and changes over the Greater Horn of Africa, *International Journal of Climatology*, 32, 347–363, doi:10.1002/joc.2270, URL <http://doi.wiley.com/10.1002/joc.2270>, 2012.
- Anyah, R. O., Semazzi, F. H. M., and Xie, L.: Simulated Physical Mechanisms Associated with Climate Variability over Lake Victoria Basin in East Africa, *Monthly Weather Review*, 134, 3588–3609, 2006.
- Bahaga, T. K., Mengistu Tsidu, G., Kucharski, F., and Diro, G. T.: Potential predictability of the sea-surface temperature forced equatorial east african short rains

- interannual variability in the 20th century, *Quarterly Journal of the Royal Meteorological Society*, 141, 16–26, doi:10.1002/qj.2338, 2015.
- Balmaseda, M., Hernandez, F., Storto, a., Palmer, M., Alves, O., Shi, L., Smith, G., Toyoda, T., Valdivieso, M., Barnier, B., Behringer, D., Boyer, T., Chang, Y.-S., Chepurin, G., Ferry, N., Forget, G., Fujii, Y., Good, S., Guinehut, S., Haines, K., Ishikawa, Y., Keeley, S., Köhl, a., Lee, T., Martin, M., Masina, S., Masuda, S., Meyssignac, B., Mogensen, K., Parent, L., Peterson, K., Tang, Y., Yin, Y., Vernieres, G., Wang, X., Waters, J., Wedd, R., Wang, O., Xue, Y., Chevallier, M., Lemieux, J.-F., Dupont, F., Kuragano, T., Kamachi, M., Awaji, T., Caltabiano, a., Wilmer-Becker, K., and Gaillard, F.: The Ocean Reanalyses Intercomparison Project (ORA-IP), *Journal of Operational Oceanography*, 8, s80–s97, doi: 10.1080/1755876X.2015.1022329, URL <http://www.tandfonline.com/doi/full/10.1080/1755876X.2015.1022329>, 2015.
- Balsamo, G., Beljaars, A., Scipal, K., Viterbo, P., van den Hurk, B., Hirschi, M., and Betts, A. K.: A Revised Hydrology for the ECMWF Model: Verification from Field Site to Terrestrial Water Storage and Impact in the Integrated Forecast System, *Journal of Hydrometeorology*, 10, 623–643, doi:10.1175/2008JHM1068.1, 2009.
- Barkmeijer, J., Iversen, T., and Palmer, T. N.: Forcing singular vectors and other sensitive model structures, *Quarterly Journal of the Royal Meteorological Society*, 129, 2401–2423, doi:10.1256/qj.02.126, URL <http://doi.wiley.com/10.1256/qj.02.126>, 2003.
- Becht, R. and Harper, D. M.: Towards an understanding of human impact upon the hydrology of Lake Naivasha , Kenya, *Hydrobiologia*, 488, 1–11, 2002.
- Behera, S. K., Krishnan, R., and Yamagata, T.: Unusual ocean-atmosphere Indian Ocean during 1994 conditions in the tropical Wind Anomalies, *Geophysical Research Letters*, 26, 3001–3004, 1999.
- Berger, A.: Long-term variations of daily insolation and Quaternary climatic changes, *Journal of the Atmospheric Sciences*, 35, 2363–2367, doi: [http://dx.doi.org/10.1175/1520-0469\(1978\)035<2362:LTVODI>2.0.CO;2](http://dx.doi.org/10.1175/1520-0469(1978)035<2362:LTVODI>2.0.CO;2), URL [http://journals.ametsoc.org/doi/abs/10.1175/1520-0469\(1978\)035{ }3C2362{ }3ALTVOI{ }3E2.0.CO{ }3B2](http://journals.ametsoc.org/doi/abs/10.1175/1520-0469(1978)035{ }3C2362{ }3ALTVOI{ }3E2.0.CO{ }3B2), 1978.
- Berger, A., Loutre, M.-F., and Tricot, C.: Insolation and Earth's orbital periods, *Journal of Geophysical Research*, 98, 10 341–10 362, doi:10.1029/93JD00222, 1993.
- Bhend, J., Franke, J., Folini, D., Wild, M., and Brönnimann, S.: An ensemble-based approach to climate reconstructions, *Climate of the Past*, 8, 963–976, doi:10.5194/cp-8-963-2012, 2012.

- Bjerknes, J.: Atmospheric Teleconnections From The Equatorial Pacific, *Monthly Weather Review*, 97, 163–172, doi:10.1175/1520-0493(1969)097<0163:ATFTEP>2.3.CO;2, URL [http://journals.ametsoc.org/doi/abs/10.1175/1520-0493\(1969\)097<0163:ATFTEP>2.3.CO;2](http://journals.ametsoc.org/doi/abs/10.1175/1520-0493(1969)097<0163:ATFTEP>2.3.CO;2), 1969.
- Black, E.: The relationship between Indian Ocean sea-surface temperature and East African rainfall., *Philosophical transactions. Series A, Mathematical, physical, and engineering sciences*, 363, 43–47, doi:10.1098/rsta.2004.1474, 2005.
- Black, E., Slingo, J., and Sperber, K.: An observational study of the relationship between excessively strong short rains in coastal East Africa and Indian Ocean SST., *Monthly Weather Review*, pp. 74–94, doi:10.1175/1520-0493(2003)131<0074:AOSOTR>2.0.CO;2, URL <http://centaur.reading.ac.uk/5437/>, 2003.
- Brown, E. T. and Johnson, T. C.: Coherence between tropical East African and South American records of the Little Ice Age, *Geochemistry, Geophysics, Geosystems*, 6, 1–11, doi:10.1029/2005GC000959, 2005.
- Brown, J., Simmonds, I., and Noone, D.: Modeling d18O in tropical precipitation and the surface ocean for present-day climate, *Journal of Geophysical Research Atmospheres*, 111, 1–16, doi:10.1029/2004JD005611, 2006.
- Buckles, L. K., Weijers, J. W. H., Verschuren, D., Cocquyt, C., and Sinninghe Damsté, J. S.: Interannual and (multi-)decadal variability in the sedimentary BIT index of Lake Challa, East Africa over the past 2200 years: assessment of the precipitation proxy, *Climate of the Past*, 12, 1243–1262, doi:10.5194/cp-12-1243-2016, URL <http://www.clim-past.net/12/1243/2016/>, 2016.
- Byrs, E.: East African drought 'worst in 60 years', *Channel 4 News*, <http://www.channel4.com/news/refugee-crisis-looms-as-east-africa-drought-worsens>, accessed August 3, 2016, 2011.
- Cai, W., Zheng, X.-T., Weller, E., Collins, M., Cowan, T., Lengaigne, M., Yu, W., and Yamagata, T.: Projected response of the Indian Ocean Dipole to greenhouse warming, *Nature Geoscience*, 6, 999–1007, doi:10.1038/ngeo2009, URL <http://www.nature.com/doi/10.1038/ngeo2009>, 2013.
- Cane, M. A.: The evolution of El Niño, past and future, *Earth and Planetary Science Letters*, 230, 227–240, doi:10.1016/j.epsl.2004.12.003, 2005.
- Charles, C. D.: Interaction Between the ENSO and the Asian Monsoon in a Coral Record of Tropical Climate, *Science*, 69, 27–42, doi:10.1126/science.277.5328.925, 1997.

- Chen, M., Xie, P., Janowiak, J. E., and Arkin, P. a.: Global Land Precipitation: A 50-yr Monthly Analysis Based on Gauge Observations, *Journal of Hydrometeorology*, 3, 249–266, doi:10.1175/1525-7541(2002)003<0249:GLPAYM>2.0.CO;2, 2002.
- Clark, C., Webster, P., and Cole, J.: Interdecadal variability of the relationship between the Indian Ocean zonal mode and East African coastal rainfall anomalies, *Journal of Climate*, 16, 548–554, doi:http://dx.doi.org/10.1175/1520-0442(2003)016<0548:IVOTRB>2.0.CO;2, URL [http://journals.ametsoc.org/doi/abs/10.1175/1520-0442\(2003\)016<0548:IVOTRB>2.0.CO;2](http://journals.ametsoc.org/doi/abs/10.1175/1520-0442(2003)016<0548:IVOTRB>2.0.CO;2), 2003.
- Coats, S., Smerdon, J. E., Cook, B. I., and Seager, R.: Are Simulated Megadroughts in the North American Southwest Forced?*, *Journal of Climate*, 28, 124–142, doi:10.1175/JCLI-D-14-00071.1, URL <http://journals.ametsoc.org/doi/abs/10.1175/JCLI-D-14-00071.1>, 2015.
- Cole, J. E.: Tropical Pacific Forcing of Decadal SST Variability in the Western Indian Ocean over the Past Two Centuries, *Science*, 287, 617–619, doi:10.1126/science.287.5453.617, 2000.
- Collins, W. D., Bitz, C. M., Blackmon, M. L., Bonan, G. B., Bretherton, C. S., Carton, J. a., Chang, P., Doney, S. C., Hack, J. J., Henderson, T. B., Kiehl, J. T., Large, W. G., McKenna, D. S., Santer, B. D., and Smith, R. D.: The Community Climate System Model version 3 (CCSM3), *Journal of Climate*, 19, 2122–2143, doi:10.1175/JCLI-D-11-00290.1, URL <http://journals.ametsoc.org/doi/pdf/10.1175/JCLI3761.1>, 2006.
- Compo, G. P. and Sardeshmukh, P. D.: Removing ENSO-related variations from the climate record, *Journal of Climate*, 23, 1957–1978, doi:10.1175/2009JCLI2735.1, 2010.
- Conway, D., Hanson, C. E., Doherty, R., and Persechino, a.: GCM simulations of the Indian Ocean dipole influence on East African rainfall: Present and future, *Geophysical Research Letters*, 34, L03 705, doi:10.1029/2006GL027597, URL <http://doi.wiley.com/10.1029/2006GL027597>, 2007.
- Cook, K. H. and Vizy, E. K.: Projected changes in east african rainy seasons, *Journal of Climate*, 26, 5931–5948, doi:10.1175/JCLI-D-12-00455.1, 2013.
- Crespin, E., Goosse, H., Fichefet, T., and Mann, M. E.: The 15th century Arctic warming in coupled model simulations with data assimilation, *Climate of the Past*, 5, 389–401, doi:10.5194/cp-5-389-2009, 2009.

- Crowley, T. J. and Unterman, M. B.: Technical details concerning development of a 1200 yr proxy index for global volcanism, *Earth System Science Data*, 5, 187–197, doi:10.5194/essd-5-187-2013, 2013.
- Dee, D. P., Uppala, S. M., Simmons, A. J., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., Balmaseda, M. A., Balsamo, G., Bauer, P., Bechtold, P., Beljaars, A. C. M., van de Berg, L., Bidlot, J., Bormann, N., Delsol, C., Dragani, R., Fuentes, M., Geer, A. J., Haimberger, L., Healy, S. B., Hersbach, H., Hólm, E. V., Isaksen, I., Kallberg, P., Köhler, M., Matricardi, M., McNally, A. P., Monge-Sanz, B. M., Morcrette, J. J., Park, B. K., Peubey, C., de Rosnay, P., Tavolato, C., Thépaut, J. N., and Vitart, F.: The ERA-Interim reanalysis: Configuration and performance of the data assimilation system, *Quarterly Journal of the Royal Meteorological Society*, 137, 553–597, doi:10.1002/qj.828, 2011.
- Deutsche Welle: El Nino-induced floods ravage East Africa, Deutsche Welle (DW) News, <http://www.dw.com/en/el-nino-induced-floods-ravage-east-africa/a-19245333> (accessed August 3, 2016), 2016.
- Dinku, T., Ceccato, P., Grover-Kopec, E., Lemma, M., Connor, S. J., and Ro-pelewski, C. F.: Validation of satellite rainfall products over East Africa’s complex topography, *International Journal of Remote Sensing*, 28, 1503–1526, doi: 10.1080/01431160600954688, URL <http://www.tandfonline.com/doi/abs/10.1080/01431160600954688>, 2007.
- Dubinkina, S., Goosse, H., Sallaz-Damaz, Y., Crespin, E., and Crucifix, M.: Testing a particle filter to reconstruct climate changes over the past centuries, *International Journal of Bifurcation and Chaos*, 21, 3611–3618, doi:10.1142/S0218127411030763, 2011.
- Dufresne, J. L., Foujols, M. a., Denvil, S., Caubel, A., Marti, O., Aumont, O., Balkanski, Y., Bekki, S., Bellenger, H., Benshila, R., Bony, S., Bopp, L., Braconnot, P., Brockmann, P., Cadule, P., Cheruy, F., Codron, F., Cozic, A., Cugnet, D., de Noblet, N., Duvel, J. P., Ethé, C., Fairhead, L., Fichefet, T., Flavoni, S., Friedlingstein, P., Grandpeix, J. Y., Guez, L., Guilyardi, E., Hauglustaine, D., Hourdin, F., Idelkadi, A., Ghattas, J., Joussaume, S., Kageyama, M., Krinner, G., Labetoulle, S., Lahellec, A., Lefebvre, M. P., Lefevre, F., Levy, C., Li, Z. X., Lloyd, J., Lott, F., Madec, G., Mancip, M., Marchand, M., Masson, S., Meurdesoif, Y., Mignot, J., Musat, I., Parouty, S., Polcher, J., Rio, C., Schulz, M., Swingedouw, D., Szopa, S., Talandier, C., Terray, P., Viovy, N., and Vuichard, N.: Climate change projections using the IPSL-CM5 Earth System Model: From CMIP3 to CMIP5, *Climate Dynamics*, 40, 2123–2165, doi:10.1007/s00382-012-1636-1, 2013.

- Dutra, E., Magnusson, L., Wetterhall, F., Cloke, H. L., Balsamo, G., Boussetta, S., and Pappenberger, F.: The 2010-2011 drought in the Horn of Africa in ECMWF reanalysis and seasonal forecast products, *International Journal of Climatology*, 33, 1720–1729, doi:10.1002/joc.3545, 2013.
- Ebinger, C.: Continental break-up: the East African perspective, *Astronomy & Geophysics*, 46, 2.16–2.21, URL <http://astrogeo.oxfordjournals.org/content/46/2/2.16.short>, 2005.
- EMDAT: The international Disaster Database, <http://emdat.be> (accessed August 31, 2016), URL <http://emdat.be>, 2016.
- Evans, M. N., Kaplan, A., and Cane, M. A.: Intercomparison of coral oxygen isotope data and historical sea surface temperature (SST): Potential for coral-based SST field reconstructions, *Paleoceanography*, 15, 551–563, doi:10.1029/2000PA000498, 2000.
- Fallah, B. and Cubasch, U.: A comparison of model simulations of Asian mega-droughts during the past millennium with proxy reconstructions, *Climate of the Past Discussions*, 11, 253–263, doi:10.5194/cp-11-253-2015, URL <http://www.clim-past.net/11/253/2015/cp-11-253-2015.html>, 2015.
- FAO: Millions of people are on the brink of starvation in the Horn of Africa, Food and Agriculture Organization (FAO) News Room, <http://www.fao.org/newsroom/en/news/2006/1000206/index.html> (accessed August 2, 2016), URL <http://www.fao.org/newsroom/en/news/2006/1000206/index.html>, 2006.
- Fichefet, T. and Maqueda, M. a. M.: Sensitivity of a global sea ice model to the treatment of ice thermodynamics and dynamics, *Journal of Geophysical Research*, 102, 12 609, doi:10.1029/97JC00480, 1997.
- Flato, G., Marotzke, J., Abiodun, B., Braconnot, P., Chou, S., Collins, W., Cox, P., Driouech, F., Emori, S., Eyring, V., Forest, C., Gleckler, P., Guilyardi, E., Jakob, C., Kattsov, V., Reason, C., and Rummukainen, M.: Evaluation of Climate Models, in: *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by Stocker, T., Qin, D., Plattner, G.-K., Tignor, M., Allen, S., Boschung, J., Nauels, A., Xia, Y., Bex, V., and Midgley, P., Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 2013.
- Flückiger, J., Monnin, E., Stauffer, B., Schwander, J., Stocker, T. F., Chappellaz, J., Raynaud, D., and Barnola, J.-M.: High-resolution Holocene N₂O ice

- core record and its relationship with CH₄ and CO₂, *Global Biogeochemical Cycles*, 16, 1010, doi:10.1029/2001GB001417, URL <http://www.agu.org/pubs/crossref/2002/2001GB001417.shtml>, 2002.
- Funk, C., Dettinger, M. D., Michaelsen, J. C., Verdin, J. P., Brown, M. E., Barlow, M., and Hoell, A.: Warming of the Indian Ocean threatens eastern and southern African food security but could be mitigated by agricultural development, *Proceedings of the National Academy of Sciences*, 105, 11 081–11 086, doi:10.1073/pnas.0708196105, URL <http://www.pnas.org/content/105/32/11081.abstract>, 2008.
- Funk, C., Hoell, A., Shukla, S., Bladé, I., Liebmann, B., Roberts, J. B., Robertson, F. R., and Husak, G.: Predicting East African spring droughts using Pacific and Indian Ocean sea surface temperature indices, *Hydrology and Earth System Sciences*, 18, 4965–4978, doi:10.5194/hess-18-4965-2014, 2014.
- Gao, C., Robock, A., and Ammann, C.: Volcanic forcing of climate over the past 1500 years: An improved ice core-based index for climate models, *Journal of Geophysical Research: Atmospheres*, 113, 1–15, doi:10.1029/2008JD010239, 2008.
- Gao, X., Xu, Y., Zhao, Z., Pal, J. S., and Giorgi, F.: On the role of resolution and topography in the simulation of East Asia precipitation, *Theoretical and Applied Climatology*, 86, 173–185, doi:10.1007/s00704-005-0214-4, 2006.
- Garcin, Y., Williamson, D., Taieb, M., Vincens, A., Mathé, P. E., and Majule, A.: Centennial to millennial changes in maar-lake deposition during the last 45,000 years in tropical Southern Africa (Lake Masoko, Tanzania), *Palaeogeography, Palaeoclimatology, Palaeoecology*, 239, 334–354, doi:10.1016/j.palaeo.2006.02.002, 2006.
- Garcin, Y., Williamson, D., Bergonzini, L., Radakovitch, O., Vincens, A., Buchet, G., Guiot, J., Brewer, S., Mathé, P. E., and Majule, A.: Solar and anthropogenic imprints on Lake Masoko (southern Tanzania) during the last 500 years, *Journal of Paleolimnology*, 37, 475–490, doi:10.1007/s10933-006-9033-6, 2007.
- Giorgetta, M. A., Jungclaus, J. H., Reick, C. H., Legutke, S., Bader, J., Böttinger, M., Brovkin, V., Crueger, T., Esch, M., Fieg, K., Glushak, K., Gayler, V., Haak, H., Hollweg, H.-D., Ilyina, T., Kinne, S., Kornblueh, L., Matei, D., Mauritsen, T., Mikolajewicz, U., Mueller, W., Notz, D., Pithan, F., Raddatz, T., Rast, S., Redler, R., Roeckner, E., Schmidt, H., Schnur, R., Segschneider, J., Six, K. D., Stockhause, M., Timmreck, C., Wegner, J., Widmann, H., Wieners, K.-H., Claussen, M., Marotzke, J., and Stevens, B.: Climate and carbon cycle changes from 1850 to 2100 in MPI-ESM simulations for the coupled model intercomparison project phase 5,

- Journal of Advances in Modeling Earth Systems, 5, 572–597, doi:10.1002/jame.20038, URL <http://doi.wiley.com/10.1002/jame.20038>, 2013.
- Goddard, L. and Graham, N. E.: Importance of the Indian Ocean for simulating rainfall anomalies over eastern and southern Africa, *Journal of Geophysical Research*, 104, 19 099, doi:10.1029/1999JD900326, URL <http://doi.wiley.com/10.1029/1999JD900326>, 1999.
- Goosse, H., Renssen, H., Timmermann, A., and Bradley, R. S.: Internal and forced climate variability during the last millennium: a model-data comparison using ensemble simulations, *Quaternary Science Reviews*, 24, 1345–1360, 2005.
- Goosse, H., Renssen, H., Timmermann, A., Bradley, R. S., and Mann, M. E.: Using paleoclimate proxy-data to select optimal realisations in an ensemble of simulations of the climate of the past millennium, *Climate Dynamics*, 27, 165–184, doi:10.1007/s00382-006-0128-6, 2006.
- Goosse, H., Brovkin, V., Fichet, T., Haarsma, R., Huybrechts, P., Jongma, J., Mouchet, a., Selten, F., Barriat, P.-Y., Campin, J.-M., Deleersnijder, E., Driesschaert, E., Goelzer, H., Janssens, I., Loutre, M.-F., Morales Maqueda, M. a., Opsteegh, T., Mathieu, P.-P., Munhoven, G., Pettersson, E. J., Renssen, H., Roche, D. M., Schaeffer, M., Tartinvill, B., Timmermann, a., and Weber, S. L.: Description of the Earth system model of intermediate complexity LOVECLIM version 1.2, *Geoscientific Model Development*, 3, 603–633, doi:10.5194/gmd-3-603-2010, URL <http://www.geosci-model-dev.net/3/603/2010/>, 2010.
- Goosse, H., Guiot, J., Mann, M. E., Dubinkina, S., and Sallaz-Damaz, Y.: The medieval climate anomaly in Europe: Comparison of the summer and annual mean signals in two reconstructions and in simulations with data assimilation, *Global and Planetary Change*, xxx, xxx—xxx, 2011.
- Goosse, H., Crespin, E., Dubinkina, S., Loutre, M.-F., Mann, M. E., Renssen, H., Sallaz-damaz, Y., and Shindell, D.: The role of forcing and internal dynamics in explaining the "Medieval Climate Anomaly", *Climate Dynamics*, 2012.
- Hakim, G. J., Emile-Geay, J., Steig, E. J., Noone, D., Anderson, D. M., Tardif, R., Steiger, N., and Perkins, W. A.: The Last Millennium Climate Reanalysis Project: Framework and First Results, *Journal of Geophysical Research: Atmospheres*, doi:10.1002/2016JD024751, URL <http://doi.wiley.com/10.1002/2016JD024751>, 2016.
- Hansen, J. and Sato, M.: Greenhouse gas growth rates., *Proceedings of the National Academy of Sciences of the United States of America*, 101, 16 109–16 114, doi: 10.1073/pnas.0406982101, 2004.

- Hartmann, D., Klein Tank, A., Rusticucci, M., Alexander, L. V., Brönnimann, S., Charabi, Y., Dentener, F. J., Dlugokencky, E. J., Easterling, D. R., Kaplan, A., Soden, B. J., Thorne, P. W., Wild, M., and Zhai, P. M.: Observations: Atmosphere and Surface, in: *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by Stocker, T. F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S., Boschung, J., Nauels, A., Xia, Y., Bex, V., and Midgley, P., pp. 159–254, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, doi:10.1017/CBO9781107415324.008, 2013.
- Hastenrath, S., Nicklis, A., and Greischar, L.: Atmospheric-hydrospheric mechanisms of climate anomalies in the western equatorial Indian Ocean, *Journal of Geophysical Research*, 96, 20 219–20 235, 1993.
- Hastenrath, S., Polzin, D., and Camberlin, P.: Exploring the predictability of the 'Short Rains' at the Coast of East Africa, *International Journal of Climatology*, 24, 1333–1343, doi:10.1002/joc.1070, 2004.
- Hastenrath, S., Polzin, D., and Mutai, C.: Diagnosing the 2005 drought in equatorial East Africa, *Journal of Climate*, 20, 4628–4637, doi:10.1175/JCLI4238.1, 2007.
- Hazeleger, W., Wang, X., Severijns, C., Stefanescu, S., Bintanja, R., Sterl, A., Wyser, K., Semmler, T., Yang, S., van den Hurk, B., van Noije, T., van der Linden, E., and van der Wiel, K.: EC-Earth V2.2: Description and validation of a new seamless earth system prediction model, *Climate Dynamics*, 39, 2611–2629, doi:10.1007/s00382-011-1228-5, 2012.
- Hession, S. L. and Moore, N.: A spatial regression analysis of the influence of topography on monthly rainfall in East Africa, *International Journal of Climatology*, 31, 1440–1456, doi:10.1002/joc.2174, 2011.
- Hillbruner, C. and Moloney, G.: When early warning is not enough-Lessons learned from the 2011 Somalia Famine, *Global Food Security*, 1, 20–28, doi:10.1016/j.gfs.2012.08.001, URL <http://linkinghub.elsevier.com/retrieve/pii/S2211912412000107>, 2012.
- Hoell, A., Funk, C., and Barlow, M.: The regional forcing of Northern hemisphere drought during recent warm tropical west Pacific Ocean La Niña events, *Climate Dynamics*, 42, 3289–3311, doi:10.1007/s00382-013-1799-4, URL <http://link.springer.com/10.1007/s00382-013-1799-4>, 2014.
- Huffman, G. J., Adler, R. F., Bolvin, D. T., and Gu, G.: Improving the global precipitation record: GPCP Version 2.1, *Geophysical Research Letters*, 36, 1–5, doi:10.1029/2009GL040000, 2009.

- Hurrell, J. W., Holland, M. M., Gent, P. R., Ghan, S., Kay, J. E., Kushner, P. J., Lamarque, J. F., Large, W. G., Lawrence, D., Lindsay, K., Lipscomb, W. H., Long, M. C., Mahowald, N., Marsh, D. R., Neale, R. B., Rasch, P., Vavrus, S., Vertenstein, M., Bader, D., Collins, W. D., Hack, J. J., Kiehl, J., and Marshall, S.: The community earth system model: A framework for collaborative research, *Bulletin of the American Meteorological Society*, 94, 1339–1360, doi:10.1175/BAMS-D-12-00121.1, 2013.
- Hurt, G. C., Chini, L. P., Froking, S., Betts, R. a., Feddema, J., Fischer, G., Fisk, J. P., Hibbard, K., Houghton, R. a., Janetos, a., Jones, C. D., Kindermann, G., Kinoshita, T., Klein Goldewijk, K., Riahi, K., Shevliakova, E., Smith, S., Stehfest, E., Thomson, a., Thornton, P., van Vuuren, D. P., and Wang, Y. P.: Harmonization of land-use scenarios for the period 1500–2100: 600 years of global gridded annual land-use transitions, wood harvest, and resulting secondary lands, *Climatic Change*, 109, 117–161, doi:10.1007/s10584-011-0153-2, 2011.
- IFRC: Eastern Africa: worst floods in decades, International Federation of Red Cross and Red Crescent Societies (IFRC) News, <http://www.ifrc.org/fr/nouvelles/nouvelles/common/eastern-africa-worst-floods-in-decades> (accessed August 3, 2016), 2007.
- IFRC: Drought in the Horn of Africa - Preventing the next disaster, Tech. rep., International Federation of Red Cross and Red Crescent Societies, 2011.
- IFRC: Disaster relief emergency fund (DREF) - Kenya : Floods 2012, Tech. rep., International Federation of Red Cross and Red Crescent Societies, 2013a.
- IFRC: Emergency appeal - Kenya : Floods 2013, Tech. Rep. April 2013, International Federation of Red Cross and Red Crescent Societies, 2013b.
- Indeje, M., Semazzi, F. H., and Ogallo, L. J.: ENSO signals in East African rainfall seasons, *International Journal of Climatology*, 20, 19–46, doi:10.1002/(SICI)1097-0088(200001)20:1<19::AID-JOC449>3.0.CO;2-0, 2000.
- IRI: Emerging La Nina conditions in the equatorial Pacific: Notes for the Health Community, Tech. rep., The International Research Institute for Climate and Society, 2010.
- IRIN: Floods affect tens of thousands, Integrated Regional Information Networks (IRIN) News, <http://www.irinnews.org/news/2012/10/08> (accessed August 3, 2016), 2012.

- IRIN: In East Africa, heavy rains test emergency preparedness, Integrated Regional Information Networks (IRIN) News, <http://www.irinnews.org/news/2013/04/11> (accessed August 3, 2016), 2013.
- Izumo, T., Lengaigne, M., Vialard, J., Luo, J.-J., Yamagata, T., and Madec, G.: Influence of Indian Ocean Dipole and Pacific recharge on following year's El Nino: interdecadal robustness, *Climate Dynamics*, 42, 291–310, doi:10.1007/s00382-012-1628-1, URL <http://link.springer.com/10.1007/s00382-012-1628-1>, 2014.
- JAMSTEC: Seasonal Prediction: ENSO forecast, Indian Ocean forecast, Regional forecast, URL http://www.jamstec.go.jp/frcgc/research/d1/iod/sintex{_f1{_}announcements{_}s.html.en, 2015.
- Johnson, T. C. and McCave, I. N.: Transport mechanism and paleoclimatic significance of terrigenous silt deposited in varved sediments of an African rift lake, *Limnology and Oceanography*, 53, 1622–1632, doi:10.4319/lo.2008.53.4.1622, 2008.
- Juillet-Leclerc, A. and Schmidt, G.: A calibration of the oxygen isotope paleothermometer of coral aragonite from Porites, *Geophysical Research Letters*, 28, 4135–4138, doi:10.1029/2000GL012538, 2001.
- Jungclauss, J. H., Lorenz, S. J., Timmreck, C., Reick, C. H., Brovkin, V., Six, K., Segschneider, J., Giorgetta, M. A., Crowley, T. J., Pongratz, J., Krivova, N. A., Vieira, L. E., Solanki, S. K., Klocke, D., Botzet, M., Esch, M., Gayler, V., Haak, H., Raddatz, T. J., Roeckner, E., Schnur, R., Widmann, H., Claussen, M., Stevens, B., and Marotzke, J.: Climate and carbon-cycle variability over the last millennium, *Climate of the Past*, 6, 723–737, doi:10.5194/cp-6-723-2010, 2010.
- Jury, M. R. and Huang, B.: The Rossby wave as a key mechanism of Indian Ocean climate variability, *Deep Sea Research Part I: Oceanographic Research Papers*, 51, 2123–2136, doi:10.1016/j.dsr.2004.06.005, 2004.
- Kelley, C., Ting, M., Seager, R., and Kushnir, Y.: The relative contributions of radiative forcing and internal climate variability to the late 20th Century winter drying of the Mediterranean region, *Climate Dynamics*, 38, 2001–2015, doi:10.1007/s00382-011-1221-z, 2012.
- Kennedy, J. J., A, R. N., Smith, R. O., Parker, D. E., and Saunby, M.: Reassessing biases and other uncertainties in sea surface temperature observations measured in situ since 1850: 1. Measurement and sampling uncertainties, *Journal of Geophysical Research: Atmospheres*, 116, 1–13, doi:10.1029/2010JD015218, 2011a.

- Kennedy, J. J., Rayner N A, Smith, R. O., Parker, D. E., and Saunby, M.: Reassessing biases and other uncertainties in sea surface temperature observations measured in situ since 1850: 2. Biases and homogenization, *Journal of Geophysical Research: Atmospheres*, 116, 1–22, doi:doi:10.1029/2010JD015220, 2011b.
- Kinuthia, J. H.: Horizontal and vertical structure of the Lake Turkana jet, URL <http://cat.inist.fr/?aModele=afficheN{&}cpsidt=4356156>, 1992.
- Kirtman, B., Power, S., Adedoyin, J., Boer, G., Bojariu, R., Camilloni, I., Doblas-Reyes, F., Fiore, A., Kimoto, M., Meehl, G., Prather, M., Sarr, A., Schär, C., Sutton, R., van Oldenborgh, G., Vecchi, G., and Wang, H.: Near-term climate change: projections and predictability, in: *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by Stocker, T., Qin, D., Plattner, G.-K., Tignor, M., Allen, S., Boschung, J., Nauels, A., Xia, Y., Bex, V., and Midgl, P., Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, URL <http://www.ipcc.ch/pdf/assessment-report/ar5/wg1/WG1AR5{ }Chapter11{ }FINAL.pdf>, 2013.
- Klein, F., Goosse, H., Mairesse, A., and de Vernal, A.: Model-data comparison and data assimilation of mid-Holocene Arctic sea-ice concentration, *Climate of the Past Discussions*, 9, 6515–6549, doi:10.5194/cpd-9-6515-2013, 2013.
- Klein, F., Goosse, H., Mairesse, A., and de Vernal, A.: Model-data comparison and data assimilation of mid-Holocene Arctic sea ice concentration, *Climate of the Past*, 10, 1145–1163, doi:10.5194/cp-10-1145-2014, URL <http://www.clim-past.net/10/1145/2014/>, 2014.
- Klein, F., Goosse, H., Graham, N. E., and Verschuren, D.: Comparison of simulated and reconstructed variations in East African hydroclimate over the last millennium, *Climate of the Past*, 12, 1499–1518, doi:10.5194/cp-12-1499-2016, URL <http://www.clim-past.net/12/1499/2016/>, 2016.
- Klein, S., Soden, B., and Lau, N.: Remote sea surface temperature variations during ENSO: Evidence for a tropical atmospheric bridge, *Journal of Climate*, 12, 917–932, doi:http://dx.doi.org/10.1175/1520-0442(1999)012<0917:RSSTVD>2.0.CO;2, URL [http://journals.ametsoc.org/doi/abs/10.1175/1520-0442\(1999\)012{ }3C0917:RSSTVD{ }3E2.0.CO;2](http://journals.ametsoc.org/doi/abs/10.1175/1520-0442(1999)012{ }3C0917:RSSTVD{ }3E2.0.CO;2), 1999.
- Klein Goldewijk, K. and van Drecht, G.: HYDE3: Current and historical population and land cover, in: *Integrated Modelling of Global Environmental Change*,

- An Overview of IMAGE 2.4, edited by Bouwman, A. F., Kram, T., and Goldewijk, K. K., chap. 6, pp. 93–112, Netherlands Environmental Assessment Agency, Bilthoven, Netherlands, 2006.
- Kuhnert, H., Pätzold, J., Hatcher, B., Wyrwoll, K. H., Eisenhauer, A., Collins, L. B., Zhu, Z. R., and Wefer, G.: A 200-year coral stable oxygen isotope record from a high-latitude reef off Western Australia, *Coral Reefs*, 18, 1–12, doi:10.1007/s003380050147, 1999.
- Laîné, a., Nakamura, H., Nishii, K., and Miyasaka, T.: A diagnostic study of future evaporation changes projected in CMIP5 climate models, *Climate Dynamics*, 42, 2745–2761, doi:10.1007/s00382-014-2087-7, 2014.
- Lamarque, J. F., Bond, T. C., Eyring, V., Granier, C., Heil, a., Klimont, Z., Lee, D., Liousse, C., Mieville, a., Owen, B., Schultz, M. G., Shindell, D., Smith, S. J., Stehfest, E., Van Aardenne, J., Cooper, O. R., Kainuma, M., Mahowald, N., McConnell, J. R., Naik, V., Riahi, K., and Van Vuuren, D. P.: Historical (1850–2000) gridded anthropogenic and biomass burning emissions of reactive gases and aerosols: Methodology and application, *Atmospheric Chemistry and Physics*, 10, 7017–7039, doi:10.5194/acp-10-7017-2010, 2010.
- Landrum, L., Otto-Bliesner, B. L., Wahl, E. R., Conley, A., Lawrence, P. J., Rosenbloom, N., and Teng, H.: Last millennium climate and its variability in CCSM4, *Journal of Climate*, 26, 1085–1111, doi:10.1175/JCLI-D-11-00326.1, 2013.
- Latif, M. and Barnett, T. P.: Interactions of the tropical oceans, doi:10.1175/1520-0442(1995)008<0952:IOTTO>2.0.CO;2, 1995.
- Latif, M., Dommenges, D., Dima, M., and Grötzner, A.: The Role of Indian Ocean Sea Surface Temperature in Forcing East African Rainfall Anomalies during December–January 1997/98, *American Meteorological Society*, 12, 3497–3504, doi:http://dx.doi.org/10.1175/1520-0442(1999)012<3497:TROIOS>2.0.CO;2, 1999.
- Lau, K.-M. and Yang, S.: Walker circulation, Academic press, San Diego, California, 2002.
- L’Heureux, M. L., Lee, S., and Lyon, B.: Recent multidecadal strengthening of the Walker circulation across the tropical Pacific, *Nature Climate Change*, 3, 1–6, doi:10.1038/nclimate1840, URL <http://www.nature.com/doifinder/10.1038/nclimate1840>, 2013.
- Li, T., Wang, B., Chang, C.-P., and Zhang, Y.: A Theory for the Indian Ocean Dipole-Zonal Mode*, *Journal of the Atmospheric Sciences*, 60, 2119–2135, doi:10.1175/1520-0469(2003)060<2119:ATFTIO>2.0.CO;2, 2003.

- Liebmann, B., Hoerling, M. P., Funk, C., Bladé, I., Dole, R. M., Allured, D., Quan, X., Pegion, P., and Eischeid, J. K.: Understanding recent eastern Horn of Africa rainfall variability and change, *Journal of Climate*, 27, 8630–8645, doi:10.1175/JCLI-D-13-00714.1, 2014.
- Lyon, B.: Seasonal Drought in the Greater Horn of Africa and Its Recent Increase during the March-May Long Rains, *Journal of Climate*, 27, 7953–7975, doi:10.1175/JCLI-D-13-00459.1, URL <http://journals.ametsoc.org/doi/abs/10.1175/JCLI-D-13-00459.1>, 2014.
- Lyon, B. and DeWitt, D. G.: A recent and abrupt decline in the East African long rains, *Geophysical Research Letters*, 39, 1–5, doi:10.1029/2011GL050337, URL <http://www.agu.org/pubs/crossref/2012/2011GL050337.shtml>, 2012.
- MacFarling Meure, C., Etheridge, D., Trudinger, C., Steele, P., Langenfelds, R., Van Ommen, T., Smith, a., and Elkins, J.: Law Dome CO₂, CH₄ and N₂O ice core records extended to 2000 years BP, *Geophysical Research Letters*, 33, 2000–2003, doi:10.1029/2006GL026152, 2006.
- Madec, G.: NEMO reference manual, ocean dynamics component: NEMO- OPA. Note du Pole de modélisation, Institut Pierre-Simon Laplace (IPSL), France, No. 27 ISSN No. 1288-1619. Available from: <http://www.lodyc.jussieu.fr/NEMO/general/manual/NEMO_book.pdf>, 2008.
- Mairesse, A., Goosse, H., Mathiot, P., Wanner, H., and Dubinkina, S.: Investigating the consistency between proxy-based reconstructions and climate models using data assimilation: a mid-Holocene case study, *Climate of the Past*, 9, 2741–2757, doi:10.5194/cp-9-2741-2013, URL <http://www.clim-past.net/9/2741/2013/cp-9-2741-2013.html>, 2013.
- Masih, I., Maskey, S., Mussá, F. E. F., and Trambauer, P.: A review of droughts on the African continent: A geospatial and long-term perspective, *Hydrology and Earth System Sciences*, 18, 3635–3649, doi:10.5194/hess-18-3635-2014, 2014.
- Mason, S. J. and Goddard, L. M.: Probabilistic Precipitation Anomalies Associated with ENSO, *Bulletin of the American Meteorological Society*, 82, 619–638, doi:10.7916/D82Z15G1, 2001.
- Matsikaris, A., Widmann, M., and Jungclaus, J.: On-line and off-line data assimilation in palaeoclimatology: A case study, *Climate of the Past*, 11, 81–93, doi:10.5194/cp-11-81-2015, 2015.
- McHugh, M. J.: Multi-model trends in East African rainfall associated with increased CO₂, *Geophysical Research Letters*, 32, 1–4, doi:10.1029/2004GL021632, 2005.

- McHugh, M. J.: Impact of South Pacific circulation variability on east African rainfall, *International Journal of Climatology*, 26, 505–521, doi:10.1002/joc.1257, URL <http://doi.wiley.com/10.1002/joc.1257>, 2006.
- McPhaden, M. J., Zebiak, S. E., and Glantz, M. H.: ENSO as an integrating concept in earth science., *Science* (New York, N.Y.), 314, 1740–1745, doi:10.1126/science.1132588, 2006.
- Merrifield, M. a.: A Shift in Western Tropical Pacific Sea Level Trends during the 1990s, *Journal of Climate*, 24, 4126–4138, doi:10.1175/2011JCLI3932.1, URL <http://journals.ametsoc.org/doi/abs/10.1175/2011JCLI3932.1>, 2011.
- Meyers, G., McIntosh, P., Pigot, L., and Pook, M.: The years of El Niño, La Niña and interactions with the tropical Indian Ocean, *Journal of Climate*, 20, 2872–2880, doi:10.1175/JCLI4152.1, 2007.
- Mutai, C. and Ward, M.: East African rainfall and the tropical circulation/convection on intraseasonal to interannual timescales, *Journal of Climate*, 13, 3915–3939, doi: [http://dx.doi.org/10.1175/1520-0442\(2000\)013<3915:EARATT>2.0.CO;2](http://dx.doi.org/10.1175/1520-0442(2000)013<3915:EARATT>2.0.CO;2), URL [http://journals.ametsoc.org/doi/abs/10.1175/1520-0442\(2000\)013<3915:EARATT>2.0.CO;2](http://journals.ametsoc.org/doi/abs/10.1175/1520-0442(2000)013<3915:EARATT>2.0.CO;2), 2000.
- Mutai, C. C., Ward, M. N., and Colman, a. W.: Towards the prediction of the East Africa short rains based on sea-surface temperature-atmosphere coupling, *International Journal of Climatology*, 18, 975–997, doi:10.1002/(SICI)1097-0088(199807)18:9<975::AID-JOC259>3.3.CO;2-L, URL [http://onlinelibrary.wiley.com/doi/10.1002/\(SICI\)1097-0088\(199807\)18:9<975::AID-JOC259>3.0.CO;2-U/abstract\\$delimeter"026E30F\\$n<GotoISI>://000075236200003](http://onlinelibrary.wiley.com/doi/10.1002/(SICI)1097-0088(199807)18:9<975::AID-JOC259>3.0.CO;2-U/abstract$delimeter), 1998.
- Mwangi, E., Wetterhall, F., Dutra, E., Di Giuseppe, F., and Pappenberger, F.: Forecasting droughts in East Africa, *Hydrology and Earth System Sciences*, 18, 611–620, doi:10.5194/hess-18-611-2014, 2014.
- Nash, J. E. and Sutcliffe, J. V.: River flow forecasting through conceptual models part I – A discussion of principles, *Journal of Hydrology*, 10, 282–290, doi:[http://dx.doi.org/10.1016/0022-1694\(70\)90255-6](http://dx.doi.org/10.1016/0022-1694(70)90255-6), 1970.
- Nicholson, S.: A review of climate dynamics and climate variability in Eastern Africa, in: *The Limnology, Climatology and Paleoclimatology of the East African Lakes.*, edited by Johnson, T. C. and Odada, E. O., pp. 25–56, Gordon and Breach, 1996.

- Nicholson, S. and Selato, J.: The influence of La Nina on African rainfall, *International Journal of Climatology*, 20, 1761–1776, URL <http://128.186.98.10/people/nicholson/papers/lanina.pdf>, 2000.
- Nicholson, S. E.: Spatial teleconnections in African rainfall: A comparison of 19th and 20th century patterns, *The Holocene*, 24, 1840–1848, doi:10.1177/0959683614551230, URL <http://hol.sagepub.com/cgi/doi/10.1177/0959683614551230>, 2014.
- Nicholson, S. E., Dezfuli, A. K., and Klotter, D.: A two-century precipitation dataset for the continent of Africa, *Bulletin of the American Meteorological Society*, 93, 1219–1231, doi:10.1175/BAMS-D-11-00212.1, 2012.
- OCHA: Eastern Africa Drought Humanitarian Report No. 3, Tech. Rep. 3, UN Office for the Coordination of Humanitarian Affairs, 2011.
- OCHA: Eastern Africa Humanitarian Bulletin, Tech. Rep. 6, UN Office for the Coordination of Humanitarian Affairs, 2012.
- OCHA: Eastern Africa: Floods Update (as of 17 May 2013), UN Office for the Coordination of Humanitarian Affairs (OCHA), <http://reliefweb.int/report/kenya/eastern-africa-floods-update-17-may-2013> (accessed August 3, 2016), 2013.
- OCHA: Ethiopia Weekly Humanitarian Bulletin, 16 May 2016, UN Office for the Coordination of Humanitarian Affairs (OCHA), <http://reliefweb.int/report/ethiopia/ethiopia-weekly-humanitarian-bulletin-16-may-2016>, (accessed August 29, 2016), 2016.
- Ogallo, L. J., Janowiak, J. E., and Halpert, M. S.: Teleconnection between Seasonal Rainfall over East Africa and Global Sea Surface Temperature Anomalies, *Journal of the Meteorological Society of Japan*, 66, 807–822, 1988.
- Otieno, V. O. and Anyah, R. O.: CMIP5 simulated climate conditions of the Greater Horn of Africa (GHA). Part 1: contemporary climate, *Climate Dynamics*, 41, 2081–2097, doi:10.1007/s00382-012-1549-z, URL <http://link.springer.com/10.1007/s00382-012-1549-z>, 2012.
- Otieno, V. O. and Anyah, R. O.: CMIP5 simulated climate conditions of the Greater Horn of Africa (GHA). Part II: projected climate, *Climate Dynamics*, 41, 2099–2113, doi:10.1007/s00382-013-1694-z, URL <http://link.springer.com/10.1007/s00382-013-1694-z>, 2013.

- Otto-Bliesner, B. L., Joussaume, S., Braconnot, P., Harrison, S. P., and Abe-Ouchi, A.: Modeling and Data Syntheses of Past Climates: Paleoclimate Modelling Inter-comparison Project Phase II Workshop, Eos, Transactions American Geophysical Union, 90, 2009.
- Otto-Bliesner, B. L., Brady, E. C., Fasullo, J., Jahn, A., Landrum, L., Stevenson, S., Rosenbloom, N., Mai, A., and Strand, G.: Climate Variability and Change since 850 C.E.: An Ensemble Approach with the Community Earth System Model (CESM), Bull. Amer. Meteor. Soc., in press, doi:10.1175/BAMS-D-14-00233.1, 2015.
- Owiti, Z. and Zhu, W.: Spatial distribution of rainfall seasonality over East Africa, Journal of Geography and Regional Planning Vol., 5, 409–421, doi:10.5897/JGRP12.027, 2012.
- PAGES 2k–PMIP3 group: Continental-scale temperature variability in PMIP3 simulations and PAGES 2k regional temperature reconstructions over the past millennium, Climate of the Past, 11, 1673–1699, doi:10.5194/cp-11-1673-2015, 2015.
- Park, S. K. and Xu, L.: Data Assimilation for Atmospheric, Oceanic and Hydrologic Applications, Springer Berlin Heidelberg, doi:10.1007/978-3-540-71056-1, 2009.
- Pfeiffer, M., Timm, O., Dullo, W. C., and Podlech, S.: Oceanic forcing of interannual and multidecadal climate variability in the southwestern Indian Ocean: Evidence from a 160 year coral isotopic record (La Réunion, 55degE, 21degS), Paleoceanography, 19, 1–14, doi:10.1029/2003PA000964, 2004.
- Pohl, B. and Camberlin, P.: Influence of the Madden-Julian Oscillation on East African rainfall: II. March-May season extremes and interannual variability, Quarterly Journal of the Royal Meteorological Society, 132, 2541–2558, doi:10.1256/qj.05.223, URL <http://doi.wiley.com/10.1256/qj.05.223>, 2006.
- Pongratz, J., Reick, C., Raddatz, T., and Claussen, M.: A reconstruction of global agricultural areas and land cover for the last millennium, Global Biogeochemical Cycles, 22, doi:10.1029/2007GB003153, 2008.
- Pongratz, J., Reick, C. H., Raddatz, T., and Claussen, M.: Effects of anthropogenic land cover change on the carbon cycle of the last millennium, Global Biogeochemical Cycles, 23, 1–13, doi:10.1029/2009GB003488, 2009.
- Roeckner, E., Arpe, K., Bengtsson, L., Brinkop, S., Dümenil, L., Esch, M., Kirk, E., Lunkeit, F., Ponater, M., Rockel, B., Sausen, R., Schleese, U., Schubert, S., and Windelband, M.: Simulation of the present-day climate with the ECHAM model: Impact of model physics and resolution. Max-Planck-Institut für Meteorologie

- No. 93. [available in <http://www.mpimet.mpg.de/en/science/models/echam.html>], Tech. rep., 1992.
- Ropelewski, C. F. and Halpert, M. S.: Global and Regional Scale Precipitation Patterns Associated with the El Niño/Southern Oscillation, doi:10.1175/1520-0493(1987)115<1606:GARSPP>2.0.CO;2, 1987.
- Rowell, D. P.: Simulating SST Teleconnections to Africa: What is the State of the Art?, *Journal of Climate*, 26, 5397–5418, doi:10.1175/JCLI-D-12-00761.1, URL <http://journals.ametsoc.org/doi/abs/10.1175/JCLI-D-12-00761.1>, 2013.
- Rowell, D. P., Booth, B. B. B., Nicholson, S. E., and Good, P.: Reconciling past and future rainfall trends over East Africa, *Journal of Climate*, 28, 9768–9788, doi:10.1175/JCLI-D-15-0140.1, 2015.
- Saji, N. H., Goswami, B. N., Vinayachandran, P. N., and Yamagata, T.: A dipole mode in the tropical Indian Ocean., *Nature*, 401, 360–3, doi:10.1038/43854, URL <http://www.ncbi.nlm.nih.gov/pubmed/16862108>, 1999.
- Schmidt, G. A., Jungclaus, J. H., Ammann, C. M., Bard, E., Braconnot, P., Crowley, T. J., Delaygue, G., Joos, F., Krivova, N. a., Muscheler, R., Otto-Bliesner, B. L., Pongratz, J., Shindell, D. T., Solanki, S. K., Steinhilber, F., and Vieira, L. E. a.: Climate forcing reconstructions for use in PMIP simulations of the last millennium (v1.0), *Geoscientific Model Development*, 4, 33–45, doi:10.5194/gmd-4-33-2011, URL <http://www.geosci-model-dev.net/4/33/2011/>, 2011.
- Schmidt, G. a., Jungclaus, J. H., Ammann, C. M., Bard, E., Braconnot, P., Crowley, T. J., Delaygue, G., Joos, F., Krivova, N. a., Muscheler, R., Otto-Bliesner, B. L., Pongratz, J., Shindell, D. T., Solanki, S. K., Steinhilber, F., and Vieira, L. E. a.: Climate forcing reconstructions for use in PMIP simulations of the Last Millennium (v1.1), *Geoscientific Model Development*, 5, 185–191, doi:10.5194/gmd-5-185-2012, 2012.
- Schmidt, G. A., Kelley, M., Nazarenko, L., Ruedy, R., Russell, G. L., Aleinov, I., Bauer, M., Bauer, S. E., Bhat, M. K., Bleck, R., Canuto, V., Chen, Y.-h., Cheng, Y., Clune, T. L., Genio, A. D., Fainchtein, R. D., Faluvegi, G., Hansen, J. E., Healy, R. J., Kiang, N. Y., Koch, D., Lacis, A. a., Legrande, A. N., Lerner, J., Lo, K. K., Matthews, E. E., Menon, S., Miller, R. L., Oinas, V., Olosa, A. O., Perlwitz, J. P., Puma, M. J., Putman, W. M., Rund, D., Romanou, A., Sato, M., Shindell, D. T., Sun, S., Syed, R. A., Tausnev, N., Tsigaridis, K., Unger, N., Voulgarakis, A., Yao,

- M.-S., and Zhang, J.: Configuration and assessment of the GISS ModelE2 contributions to the CMIP5 archive, *Journal of Advances in Modeling Earth Systems*, 6, 141–184, doi:10.1002/2013MS000265, 2014.
- Schneider, U., Becker, A., Finger, P., Meyer-Christoffer, A., Ziese, M., and Rudolf, B.: GPCP's new land surface precipitation climatology based on quality-controlled in situ data and its role in quantifying the global water cycle, *Theoretical and Applied Climatology*, 115, 15–40, doi:10.1007/s00704-013-0860-x, 2014.
- Schott, F. A., Xie, S.-P., and McCreary Jr, J. P.: Indian Ocean Circulation and Climate Variability, *Reviews of Geophysics*, 47, 1–46, doi:10.1029/2007RG000245.1, INTRODUCTION, URL <http://www.agu.org/pubs/crossref/2009/2007RG000245.shtml>, 2009.
- Schreck, C. J. and Semazzi, F. H. M.: Variability of the recent climate of eastern Africa, *International Journal of Climatology*, 24, 681–701, doi:10.1002/joc.1019, URL <http://doi.wiley.com/10.1002/joc.1019>, 2004.
- Schubert, S. D., Stewart, R. E., Wang, H., Barlow, M., Berbery, E. H., Cai, W., Hoerling, M. P., Kanikicharla, K. K., Koster, R. D., Lyon, B., Mariotti, A., Mechoso, C. R., Müller, O. V., Rodriguez-Fonseca, B., Seager, R., Senevirante, S. I., Zhang, L., and Zhou, T.: Global Meteorological Drought: A Synthesis of Current Understanding with a Focus on SST Drivers of Precipitation Deficits, *Journal of Climate*, 29, 3989–4019, doi:10.1175/JCLI-D-15-0452.1, URL <http://journals.ametsoc.org/doi/10.1175/JCLI-D-15-0452.1>, 2016.
- Seager, R., Naik, N., and Vecchi, G. a.: Thermodynamic and dynamic mechanisms for large-scale changes in the hydrological cycle in response to global warming, *Journal of Climate*, 23, 4651–4668, doi:10.1175/2010JCLI3655.1, 2010.
- Shongwe, M. E., van Oldenborgh, G. J., van den Hurk, B., and van Aalst, M.: Projected Changes in Mean and Extreme Precipitation in Africa under Global Warming. Part II: East Africa, *Journal of Climate*, 24, 3718–3733, doi:10.1175/2010JCLI2883.1, URL <http://journals.ametsoc.org/doi/abs/10.1175/2010JCLI2883.1>, 2011.
- Smith, T. M., Reynolds, R. W., Peterson, T. C., and Lawrimore, J.: Improvements to NOAA's historical merged land-ocean surface temperature analysis (1880–2006), *Journal of Climate*, 21, 2283–2296, doi:10.1175/2007JCLI2100.1, 2008.
- Steiger, N. J., Hakim, G. J., Steig, E. J., Battisti, D. S., and Roe, G. H.: Assimilation of time-averaged pseudoproxies for climate reconstruction, *Journal of Climate*, 27, 426–441, doi:10.1175/JCLI-D-12-00693.1, 2014.

- Steinhilber, F., Beer, J., and Fröhlich, C.: Total solar irradiance during the Holocene, *Geophysical Research Letters*, 36, 1–5, doi:10.1029/2009GL040142, 2009.
- Stevens, B., Giorgetta, M., Esch, M., Mauritsen, T., Crueger, T., Rast, S., Salzmann, M., Schmidt, H., Bader, J., Block, K., Brokopf, R., Fast, I., Kinne, S., Kornblueh, L., Lohmann, U., Pincus, R., Reichler, T., and Roeckner, E.: The atmospheric component of the MPI-M earth system model: ECHAM6, *Journal of Advances in Modeling Earth Systems*, 5, 1–27, doi:10.1002/jame.20015, URL <http://doi.wiley.com/10.1002/jame.20015>, 2013.
- Stevenson, S., McGregor, H. V., Phipps, S. J., and Fox-Kemper, B.: Quantifying errors in coral-based ENSO estimates: Toward improved forward modeling of $\delta^{18}\text{O}$, *Paleoceanography*, 28, 633–649, doi:10.1002/palo.20059, 2013.
- Sylla, M. B., Giorgi, F., Coppola, E., and Mariotti, L.: Uncertainties in daily rainfall over Africa: Assessment of gridded observation products and evaluation of a regional climate model simulation, *International Journal of Climatology*, 33, 1805–1817, doi:10.1002/joc.3551, 2013.
- Taylor, K. E., Stouffer, R. J., and Meehl, G. a.: An Overview of CMIP5 and the Experiment Design, *Bulletin of the American Meteorological Society*, 93, 485–498, doi:10.1175/BAMS-D-11-00094.1, URL <http://journals.ametsoc.org/doi/abs/10.1175/BAMS-D-11-00094.1>, 2012.
- Thiery, W., Davin, E., Panitz, H.-j., Demuzere, M., Lhermitte, S., and Van Lipzig, N.: The impact of the African Great Lakes on the regional climate, *Journal of Climate*, 28, 4061–4085, doi:10.1175/JCLI-D-14-00565.1, 2015.
- Thompson, D. M., Ault, T. R., Evans, M. N., Cole, J. E., and Emile-Geay, J.: Comparison of observed and simulated tropical climate trends using a forward model of coral $\delta^{18}\text{O}$, *Geophysical Research Letters*, 38, 1–6, doi:10.1029/2011GL048224, 2011.
- Tierney, J. E., Russell, J. M., Sinninghe Damsté, J. S., Huang, Y., and Verschuren, D.: Late Quaternary behavior of the East African monsoon and the importance of the Congo Air Boundary, *Quaternary Science Reviews*, 30, 798–807, doi:10.1016/j.quascirev.2011.01.017, URL <http://linkinghub.elsevier.com/retrieve/pii/S0277379111000321>, 2011.
- Tierney, J. E., Smerdon, J. E., Anchukaitis, K. J., and Seager, R.: Multidecadal variability in East African hydroclimate controlled by the Indian Ocean., *Nature*, 493, 389–92, doi:10.1038/nature11785, URL <http://www.ncbi.nlm.nih.gov/pubmed/23325220>, 2013.

- Tierney, J. E., Abram, N. J., Anchukaitis, K. J., Evans, M. N., Giry, C., Kilbourne, K. H., Saenger, C. P., Wu, H. C., and Zinke, J.: Tropical sea surface temperatures for the past four centuries reconstructed from coral archives, *Paleoceanography*, 30, 226–252, doi:10.1002/2014PA002717, 2015.
- Tokinaga, H. and Tanimoto, Y.: Seasonal transition of SST anomalies in the Tropical Indian Ocean during El Niño and Indian Ocean Dipole years, *Journal of the Meteorological Society of Japan*, 82, 1007–1018, doi:10.2151/jmsj.2004.1007, 2004.
- Tourre, Y. M. and White, W. B.: ENSO Signals in Global Upper-Ocean Temperature, doi:10.1175/1520-0485(1995)025<1317:ESIGUO>2.0.CO;2, 1995.
- Ummenhofer, C. C., Sen Gupta, A., England, M. H., and Reason, C. J. C.: Contributions of Indian Ocean Sea Surface Temperatures to Enhanced East African Rainfall, *Journal of Climate*, 22, 993–1013, doi:10.1175/2008JCLI2493.1, URL <http://journals.ametsoc.org/doi/abs/10.1175/2008JCLI2493.1>, 2009.
- Valcke, S.: OASIS3 user guide. PRISM Tech. Rep 3, 64 pp. Available online at <http://www.prism.enes.org/Publications/Reports/oasis3_UserGuide_T3.pdf>, 2006.
- van Leeuwen, P. J.: Particle Filtering in Geophysical Systems, *Monthly Weather Review*, 137, 4089–4114, doi:10.1175/2009MWR2835.1, URL <http://journals.ametsoc.org/doi/abs/10.1175/2009MWR2835.1>, 2009.
- Vecchi, G. a. and Soden, B. J.: Global Warming and the Weakening of the Tropical Circulation, *Journal of Climate*, 20, 4316–4340, doi:10.1175/JCLI4258.1, URL <http://journals.ametsoc.org/doi/abs/10.1175/JCLI4258.1>, 2007.
- Vecchi, G. a., Soden, B. J., Wittenberg, A. T., Held, I. M., Leetmaa, A., and Harrison, M. J.: Weakening of tropical Pacific atmospheric circulation due to anthropogenic forcing., *Nature*, 441, 73–6, doi:10.1038/nature04744, URL <http://www.ncbi.nlm.nih.gov/pubmed/16672967>, 2006.
- Venzke, S., Latif, M., and Villwock, A.: The coupled GCM ECHO-2. Part II: Indian Ocean response to ENSO, *Journal of Climate*, 13, 1371–1383, doi:10.1175/1520-0442(2000)013<1371:TCGE>2.0.CO;2, 2000.
- Verschuren, D.: Reconstructing fluctuations of a shallow East African lake during the past 1800 yrs from sediment stratigraphy in a submerged crater basin, *Journal of Paleolimnology*, 25, 297–311, doi:10.1023/A:1011150300252, 2001.
- Verschuren, D.: Lake-based climate reconstruction in Africa: Progress and challenges, *Hydrobiologia*, 500, 315–330, doi:10.1023/A:1024686229778, 2003.

- Verschuren, D.: Decadal and century-scale climate variability in tropical Africa during the past 2000 years, in: *Past Climate Variability through Europe and Africa*, edited by Battarbee, R. W., Gasse, F., and Stickley, C. E., chap. 8, pp. 139–158, Dordrecht, The Netherlands, Springer edn., 2004.
- Verschuren, D., Laird, K. R., and Cumming, B. F.: Rainfall and drought in equatorial east Africa during the past 1,100 years., *Nature*, 403, 410–414, doi:10.1038/35000179, 2000.
- Verschuren, D., Sinninghe Damsté, J. S., Moernaut, J., Kristen, I., Blaauw, M., Fagot, M., and Haug, G. H.: Half-precessional dynamics of monsoon rainfall near the East African Equator., *Nature*, 462, 637–41, doi:10.1038/nature08520, URL <http://www.ncbi.nlm.nih.gov/pubmed/19956257>, 2009.
- Vieira, L. E. a. and Solanki, S.: Evolution of the solar magnetic flux on time scales of years to millenia, 100, 1–13, doi:10.1051/0004-6361/200913276, URL <http://arxiv.org/abs/0911.4396>, 2009.
- Vieira, L. E. A., Solanki, S. K., Krivova, N. A., and Usoskin, I.: Evolution of the solar irradiance during the Holocene, *Astronomy and Astrophysics*, 531, 1–20, doi:10.1051/0004-6361/201015843, URL <http://arxiv.org/abs/1103.4958>, 2011.
- Viste, E. and Sorteberg, A.: Moisture transport into the Ethiopian highlands, *International Journal of Climatology*, 33, 249–263, doi:10.1002/joc.3409, 2013.
- Vizy, E. K. and Cook, K. H.: Mid-twenty-first-century changes in extreme events over northern and tropical Africa, *Journal of Climate*, 25, 5748–5767, doi:10.1175/JCLI-D-11-00693.1, 2012.
- von Storch, H., Cubasch, U., González-Rouco, J., Jones, J., Voss, R., Widmann, M., and Zorita, E.: Combining paleoclimatic evidence and GCMs by means of Data Assimilation Through Upscaling and Nudging, in: *11th Symposium on Global Climate Change Studies*, pp. 28–31, AMS Long Beach, CA, 2000.
- Wang, C. and Fiedler, P. C.: ENSO variability and the eastern tropical Pacific: A review, *Progress in Oceanography*, 69, 239–266, doi:10.1016/j.pocean.2006.03.004, 2006.
- Wang, Y., Lean, J. L., and Sheeley, Jr., N. R.: Modeling the Sun’s Magnetic Field and Irradiance since 1713, *The Astrophysical Journal*, 625, 522–538, doi:10.1086/429689, 2005.

- Weare, B. C.: A Statistical Study of the Relationships between Ocean Surface Temperatures and the Indian Monsoon, *Journal of the Atmospheric Sciences*, 36, 2279–2291, 1979.
- Webster, P. J., Moore, a. M., Loschnigg, J. P., and Leben, R. R.: Coupled ocean-atmosphere dynamics in the Indian Ocean during 1997-98., *Nature*, 401, 356–60, doi:10.1038/43848, URL <http://www.ncbi.nlm.nih.gov/pubmed/16862107>, 1999.
- Widmann, M., Goosse, H., van der Schrier, G., Schnur, R., and Barkmeijer, J.: Using data assimilation to study extratropical Northern Hemisphere climate over the last millennium, *Climate of the Past*, 6, 627–644, doi:10.5194/cp-6-627-2010, URL <http://www.clim-past.net/6/627/2010/>, 2010.
- Wilhite, D. A., Sivakumar, M. V. K., and Pulwarty, R.: Managing drought risk in a changing climate: The role of national drought policy, *Weather and Climate Extremes*, 3, 4–13, doi:10.1016/j.wace.2014.01.002, URL <http://dx.doi.org/10.1016/j.wace.2014.01.002>, 2014.
- Williams, A. P. and Funk, C.: A westward extension of the warm pool leads to a westward extension of the Walker circulation , drying eastern Africa, *Climate Dynamics*, 37, 2417–2435, doi:10.1007/s00382-010-0984-y, 2011.
- Wolff, C., Haug, G. H., Timmermann, A., Sinninghe Damsté, J. S., Brauer, A., Sigman, D. M., Cane, M. A., and Verschuren, D.: Reduced interannual rainfall variability in East Africa during the last ice age., *Science (New York, N.Y.)*, 333, 743–747, doi:10.1126/science.1203724, 2011.
- Wu, T., Song, L., Li, W., Wang, Z., Zhang, H., Xin, X., Zhang, Y., Zhang, L., Li, J., Wu, F., Liu, Y., Zhang, F., Shi, X., Chu, M., Zhang, J., Fang, Y., Wang, F., Lu, Y., Liu, X., Wei, M., Liu, Q., Zhou, W., Dong, M., Zhao, Q., Ji, J., Li, L., and Zhou, M.: An overview of BCC climate system model development and application for climate change studies, *Journal of Meteorological Research*, 28, 34–56, 2014.
- Xie, P. and Arkin, P. A.: Global Precipitation: A 17-Year Monthly Analysis Based on Gauge Observations, Satellite Estimates, and Numerical Model Outputs, *Bulletin of the American Meteorological Society*, 78, 2539–2558, doi:10.1175/1520-0477(1997)078<2539:GPAYMA>2.0.CO;2, 1997.
- Xie, S.-P., Annamalai, H., Schott, F. A., and McCreary, J. P.: Structure and Mechanisms of South Indian Ocean Climate Variability, *Journal of Climate*, 15, 864–878, doi:[http://dx.doi.org/10.1175/1520-0442\(2002\)015<0864:SAMOSI>2.0.CO;2](http://dx.doi.org/10.1175/1520-0442(2002)015<0864:SAMOSI>2.0.CO;2), 2002.

- Xie, S. P., Hu, K., Hafner, J., Tokinaga, H., Du, Y., Huang, G., and Sampe, T.: Indian Ocean capacitor effect on Indo-Western pacific climate during the summer following El Niño, *Journal of Climate*, 22, 730–747, doi:10.1175/2008JCLI2544.1, 2009.
- Yamagata, T., Behera, S. K., Luo, J.-j., Masson, S., Jury, M. R., and Rao, S. a.: Coupled Ocean-Atmosphere Variability in the Tropical Indian Ocean, in: *Earth's Climate*, pp. 1–23, *Geophysical Monograph Series 147*, wang c, xi edn., doi: 10.1029/147GM12, 2004.
- Yang, J., Liu, Q., Xie, S. P., Liu, Z., and Wu, L.: Impact of the Indian Ocean SST basin mode on the Asian summer monsoon, *Geophysical Research Letters*, 34, 1–5, doi:10.1029/2006GL028571, 2007.
- Yang, W., Seager, R., Cane, M. a., and Lyon, B.: The East African Long Rains in Observations and Models, *Journal of Climate*, 27, 7185–7202, doi:10.1175/JCLI-D-13-00447.1, URL <http://journals.ametsoc.org/doi/abs/10.1175/JCLI-D-13-00447.1>, 2014.
- Yang, W., Seager, R., Cane, M. a., and Lyon, B.: The Annual Cycle of the East African Precipitation, *Journal of Climate*, 28, 2385–2404, doi:10.1175/JCLI-D-14-00484.1, 2015.
- Zhang, G. J. and Song, X.: Parameterization of Microphysical Processes in Convective Clouds in Global Climate Models, *Meteorological Monographs - Multiscale Convection-Coupled Systems in the Tropics: A Tribute to Dr. Michio Yanai*, 56, 12.1–12.18, doi:10.1175/AMSMONOGRAPHS-D-15-0015.1, 2016.
- Zinke, J., Pfeiffer, M., Timm, O., Dullo, W. C., Kroon, D., and Thomassin, B. A.: Mayotte coral reveals hydrological changes in the western indian ocean between 1881 and 1994, *Geophysical Research Letters*, 35, 1–5, doi:10.1029/2008GL035634, 2008.
- Zinke, J., Pfeiffer, M., Timm, O., Dullo, W. C., and Brummer, G. J. A.: Western Indian Ocean marine and terrestrial records of climate variability: A review and new concepts on land-ocean interactions since AD 1660, *International Journal of Earth Sciences*, 98, 115–133, doi:10.1007/s00531-008-0365-5, 2009.

