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# MONSOON VARIABILITY OVER THE HORN OF AFRICA

# A DISSERTATION APPROVED FOR THE SCHOOL OF METEOROLOGY

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# Abstract

Over the past several decades, the Horn of Africa has been ravaged by catastrophic droughts and famines. In spite of the devastating frequent droughts and occasional floods in the region, our understanding of the region's weather and climate variability is limited. The present study represents the first exhaustive investigation of rainfall variability over the Horn of Africa at intraseasonal, seasonal, interannual, and multidecadal time-scales, and contributes substantially to the fundamental understanding of weather and climate variability in the region.

This research involves observational and modeling investigations to explore and document the space-time distribution of the major elements of weather and climate and their variability in the Horn of Africa. In particular, an exhaustive diagnostic examination is performed to identify the dominant modes of rainfall variability and the large-scale atmospheric and oceanic features that affect rainfall in the region. Building on the results of the diagnostic study, dependable short- to long-range prediction models are developed. These models are capable of predicting rainfall amounts and anomalies at a specific location or region from a few days to seasons in advance. The modeling study has identified the roles of sea surface temperatures over the Mediterranean Sea, Atlantic, and Indian Oceans in shaping rainfall variability over the Horn of Africa. The impacts of depleted vegetation resulting from poor early rains on Horn of Africa summer rainfall also are investigated and identified through model sensitivity experiments.

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# **CHAPTER 1: INTRODUCTION**

The Horn of Africa, comprised of Ethiopia, Eritrea, Djibouti, the northern parts of Somalia, and portions of Sudan bordering Ethiopia and Eritrea, is one of the least developed regions in the world. A relief map of the region is shown in Fig. 1.1. The region has a tropical monsoon climate with wide topographicinduced variations. Its complex orography features high plateaux with soaring mountains reaching 4,620 m in the Semien mountain ranges in northern Ethiopia and deep valleys descending to 125 m below mean sea level in the Denakil Depression in eastern Ethiopia.



FIGURE 1.1. Relief map covering the study region. The base map was downloaded from the NASA webpage.

Rainfed agriculture and livestock raising are the main sources of livelihood for the overwhelming majority of the population in the Horn of Africa, which now totals 130 million and is growing (Source: Website of the U.S. Intelligence 2.44% annually Agency, https://www.cia.gov/cia/publications/factbook/index.html). These socioeconomic activities are extremely vulnerable to any adverse changes in weather and climate. In fact, over the past several decades, the region has been ravaged by frequent occurrences of droughts and famines that crippled the region's economy and left millions of people starved to death.

Most of the droughts and famines that devastated the region were caused by the failure of the main (Kiremt) rains that fall during June to September (Segele and Lamb 2005). The region's fragile economy, widespread poverty, high rate of population growth, reduction in soil fertility, and the declining crop yields combine to exacerbate the adverse impacts of an otherwise manageable prolonged dry periods during the main rain season. Topping the list is our limited knowledge of the variability of summer rainfall and the lack of the understanding of the systems that control it. Such knowledge is essential in order to develop accurate prediction models. Only when meteorologists understand rainfall variability and its causes will we be able to provide accurate climate information that helps alleviate the adverse impacts of the vagaries of weather and climate, or assist in the planning and management activities needed to limit the loss of life and property and improve national food security. So far, there have not been sufficient comprehensive studies that examined the major regional atmospheric systems that control or modulate summer rainfall over the Horn of Africa. Nor have there been any reliable physically-based prediction models for the region. These needs will be the focus of the present study.

There is considerable intraseasonal and interannual variability in the monsoon rainfall across the Horn of Africa. Previous observational studies revealed some relationships between the El Niño/Southern Oscillation events and monsoonal rainfall (Camberlin 1997; Gisila et al. 2004; Segele and Lamb 2005). Such observational studies, however, are few in number and limited in scope. Likewise, most of the modeling studies that cover the region have dealt largely with the effects of land surface exchange processes on a continental scale covering Africa and southeast Asia (e.g., Cook 1997; Douville 2002; Vizy and Cook 2003). Consequently, there has not been any attempt to utilize dynamic models for weather forecasting or for climate-related studies over the Horn of Africa. Numerical climate models are suited to perform sensitivity studies and to gain insights into the physical processes that could not be obtained from observational studies. The application of dynamical models for weather forecasting or climate studies for any specific region, however, requires extensive prior tests to establish their validity and usefulness. This will be one of the objectives of this study.

Accordingly, one of the aims of this study is to assess the ability of a regional climate model to reproduce realistic precipitation patterns over the Horn of Africa. Much effort is expended to adapt the model for the region. The model then is employed to perform sensitivity studies to investigate how the atmosphere responds to different regional forcing. Another major goal of this study is to identify the dominant modes of rainfall variability and examine, identify, and document the associated large-scale circulation systems that control or modulate monsoonal rainfall over the Horn of Africa on different time-scales. The study will identify the physical and dynamical characteristics that link the large-scale circulation systems with the regional precipitation anomalies. This knowledge is the basis for developing reliable physically-based prediction models that could be used on intraseasonal to interannual time-scales. This research thus aims to contribute to the fundamental understanding of the climate system over the Horn of Africa and improve the medium (a week to less than a month) and long range (a month to seasons) forecasting capability in the region. The major goals of the study can be summarized as follows:

- Diagnostic examination of the dominant modes of observed rainfall variability;
- 2. Identification and characterization of the observed large-scale atmospheric systems and oceanic features and their connection to the Horn of Africa rainfall on different time-scales;

- Assessment of the predictability of Ethiopian summer rainfall on an observational basis and development of medium and long range empirical forecasting models;
- 4. Evaluation and adaptation of a Regional Climate Model;
- 5. Use of the Regional Climate Model to assess (a) the role of the Atlantic and Indian Ocean on the summer rainfall over the Horn of Africa and (b) the impacts of local land surface characteristics on Ethiopian monsoon.

The results of the above investigation will contribute to our fundamental knowledge of the monsoon and its variability over the Horn of Africa. In addition, the development of skillful empirical models will have strong societal value. The prediction models can help improve the climate information services that are needed to monitor and mitigate the adverse impacts of the recurring droughts and occasional floods in the region.

This Dissertation is organized as follows. A review of pertinent literature is provided in Chapter 2. Chapter 3 identifies and discusses the dominant modes of observed variability of summer rainfall and examines the physical and dynamical characteristics that link rainfall with the large-scale systems. Chapter 4 assesses the predictability of Ethiopian summer rainfall on an observational basis, and discusses the development, skill, and applicability of medium- and long-range empirical prediction models. Chapter 5 describes the latest version of the International Center for Theoretical Physics Regional Climate Model (RegCM3) and assesses its performance in reproducing monsoonal rainfall over the Horn of Africa. Results of comprehensive experiments are presented. Chapter 6 examines the effects of sea surface temperature (SST) over the Atlantic and Indian Oceans on the Horn of Africa rainfall using RegCM3 sensitivity experiments. The impacts of dry pre-monsoon land cover or depleted vegetation on the upcoming monsoon season also are assessed through RegCM3 sensitivity studies. A summary and overall conclusions are provided in Chapter 7.

# **CHAPTER 2: OVERVIEW OF PERTINENT STUDIES**

# 2.1 Preamble

This chapter provides the highlights of the large-scale evolution and variability of the greater Indian Ocean monsoon system. The review primarily is based on the vast literature available on the South Asian monsoon. It aims at developing a background on the current state of knowledge of the monsoon and its variability. We then examine the climate variability over the Horn of Africa from the perspective of the global monsoon. This is followed by a review of climate model applications over the monsoon regions. To facilitate the literature review, a brief description of the monsoon systems first will be provided.

# 2.2 Elements of the Indian Monsoon System

Krishnamurti and Bhalme (1976) documented the basic characteristics of the elements of the Indian Ocean monsoon system and their fluctuations during a near normal rainfall year over India. Variations in the intensity of the monsoon system in a given year arise from the passage of rain-producing monsoon lows and depressions, the interaction of the monsoon system with other circulations, or are due to internal monsoon dynamics. The major large-scale elements of the monsoon include the monsoon trough, the Mascarene high, the low-level crossequatorial jet, the Tibetan high, and the tropical easterly jet. Fig. 2.1 (from Krishnamurti and Bhalme 1976) schematically shows the locations of these components of the monsoon system.



FIGURE 2.1. Schematic diagram of the elements of the Indian monsoon system. From Krishnamurti and Bhalme (1976).

The monsoon trough is a surface and lower tropospheric low-pressure trough and is part of the global equatorial trough of the northern summer season, which extends from West Africa to the east coast of Indo-China (Krishnamurti and Bhalme 1976). Embedded within the near-equatorial surface low-pressure trough is the Intertropical Convergence Zone (ITCZ), which is a confluence between the northeast trade winds and the cross-equatorial flow from the Southern Hemisphere (Hastenrath 1991, p. 159; Hastenrath 2000a; Grist and Nicholson 2001). Vizy and Cook (2003) consider the monsoon trough as a bridge that potentially links precipitation co-variability between the Horn of Africa and India.

The Mascarene high is a quasi-permanent subtropical cell normally centered over the south Indian Ocean near 30°S and 30°E. Oscillations in the strength of the Mascarene high have been linked to variability of monsoon rainfall over India. The quasi-biweekly oscillation in the major monsoon components found by Krishnamurti and Bhalme (1976) shows that the Mascarene high reaches maximum intensity after a widespread monsoon rainfall event over central India. Krishnamurti and Bhalme (1976) suggested that the intensification of the Mascarene high is a consequence of the strengthening of a local meridional Hadley-type overturning resulting from widespread rainfall and the associated latent heating over India. The rising (sinking) branch of the meridional circulation is over northeastern India (the Mascarene high).

Associated with the intensification of the Mascarene high, a low-level equatorward flow develops and forms a low-level jet (LLJ) that also is known as the Somali Jet or Findlater Jet (Findlater 1969). The LLJ is a narrow southwesterly surface wind that attains a maximum strength near 1.5 km height (850 hPa), with core speeds of 12-15 m s<sup>-1</sup> (Krishnamurti and Bhalme 1976; Hastenrath 1991, p.

133; Halpern and Woiceshyn 2001). The jet is known to occasionally have speeds of 50 m s<sup>-1</sup> around the 1.5 km level near Madagascar and off the Somali coast (Krishnamurti and Bhalme 1976). The LLJ transports about half of the total global lower-tropospheric mass flow across the Equator (Hastenrath 1991, p. 136), while the downstream southwesterlies over the Arabian Sea carry much of the moisture that sustains the Indian monsoon rainfall (Rodwell 1997). Large-scale monsoon rainfall accumulation over India and Southeast Asia and wind strength over Arabia and India are highly positively correlated (Findlater 1969; Ju and Slingo 1995).

One of the prominent features of the monsoon system is the Tropical Easterly Jet (TEJ), which attains maximum wind strength at 150 hPa with the strongest winds (40-50 m s<sup>-1</sup>) being west of the southern tip of India (Krishnamurti, 1971; Krishnamurti and Bhalme 1976; Kanamitsu, and Krishnamurti 1978; Chen and van Loon 1987; Hastenrath 1991, p. 129). The TEJ forms in June and stays until September (Krishnamurti and Bhalme 1976). It extends from Indo-China to the west coast of Africa. The development and maintenance of the TEJ is connected with the zonally asymmetric heating due to the east-west land-ocean contrast across South Asia and North Africa, as well as the more zonally symmetric north-south differential heating of the upper troposphere between the elevated Tibetan plateau and the Indian Ocean surface to the south (Krishnamurti and Bhalme 1976; Chen and van Loon 1987).

It has been shown that intraseasonal-to-interannual variability in these major monsoon components modulate Indian monsoon rainfall (e.g., Krishnamurti and Bhalme 1976; Vernekar and Ji 1999). For example, on shorter time-scales, variations in the intensity of the Mascarene high, the strength of the LLJ, and the meridional pressure gradient affect monsoonal rainfall. Shorter time-scale fluctuations may be reflections of local instabilities (e.g., Krishnamurti and Bhalme 1976) or can arise from chaotic weather systems in the southern hemisphere midlatitudes (Rodwell 1997). Longer time-scale fluctuations in the monsoon components are caused by variations in global SSTs. In particular, Chen and van Loon (1987) found associations between anomalously warm surface water over the eastern and central equatorial Pacific and weakening of the low-level monsoon circulation and TEJ. This study examines how these major monsoon components relate to the Horn of Africa summer monsoon rainfall through comprehensive observational and modeling studies. In the next section, a review of the large-scale monsoon rainfall variability is provided for northern hemisphere Africa and India.

# 2.3 North African and Indian Monsoon Rainfall Variability

Summer rain (June-September) contributes 65-95 percent of the total annual rainfall over much of the Horn of Africa (Gissila et al. 2004; Segele and Lamb

2005; Korecha and Barnston 2006) and is part of the global broad-scale monsoon system (Bhatt 1989; Hastenrath 1991, pp. 182; Qian et al. 2002). The monsoon is driven primarily as a result of differential heating by the northern land and more southern ocean surfaces (Hastenrath 1991, pp. 183; Ju and Slingo 1995; Webster et al. 1998; Clark et al. 2000; Qian et al. 2002; Vizy and Cook 2003) and is most developed over the Indian subcontinent (Annamalai and Slingo, 2001; Mohanty 2005).

Previous studies have shown that there is a strong dynamical link and rainfall co-variability between India and east Africa (Bhatt 1989; Camberlin 1997; Vizy and Cook 2003). In fact, Camberlin (1997) suggested that the monsoon activity over India is a major trigger of rainfall over the Ethiopian highlands. It was argued that active/strong Indian monsoon conditions correspond to an enhanced west-east pressure gradient near the equator that favors abnormally strong westerly winds across equatorial Africa that advect moisture from the Congo Basin to Ethiopia, Uganda, and western Kenya. The author found that the summer rainfall over India and western parts of East Africa correlate strongly with correlation coefficient of +0.74. Vizy and Cook (2003) proposed a more direct link involving the monsoon trough that runs through eastern Africa and extends eastward to southern Asia, and suggested that the trough regulates the connection between East Africa and India and mediates the precipitation covariability between the two regions. When the monsoon trough is weak, dry

conditions are suggested to prevail over northern Ethiopia and western India, while a strong monsoon trough favors wetter conditions over western India and drier conditions all over Ethiopia. This argument, however, appears to contradict the above strong association found between East Africa and Indian rainfall, as it would imply that most parts of Ethiopia would remain dry regardless of the strength of the monsoon trough and rainfall conditions over western India.

On the other hand, both observational and modeling studies show less coherence between the East African and West African monsoons (Bhatt 1989; Cook 1997), especially during some pronounced wet years (Segele and Lamb 2005). Bhatt (1989) also found little similarity between West African rainfall variability and discharge fluctuations in the Nile basin. In contrast, variations in the Nile water discharges show remarkable similarity with Indian rainfall time series (Bhatt 1989). It is to be noted that the Blue Nile river of Ethiopia contributes 68 percent of the peak flow of the Nile River (Williams et al. 2003). Based on results of model simulations, Cook (1997) also suggested different rainfall mechanisms in the two regions. In East Africa, low-level convergence is almost entirely forced by mid-tropospheric condensational heating, while the same mechanism accounts for a little more than half of the convergence in West Africa. Noting that the structure of precipitation resembles the low-level convergence anomaly, she concluded that different mechanisms govern the

precipitation anomalies over western and eastern parts of North Africa. However, Segele and Lamb (2005) noted that some of the severe Ethiopian droughts are part of a continent-wide failure of the monsoon in the Soudano-Sahel Zone (10°-18°N) that extends 6000 km eastward from Senegal/Gambia/Guinea Bissau/Guinea along the Atlantic coast to Ethiopia and Eritrea in the extreme east.

The previous two paragraphs indicate some degree of association between the Horn of Africa and Indian monsoons, and less coherence between summer rainfall in East and West Africa north of the equator. Capitalizing on the similarity established between the Horn of Africa and Indian monsoons and noting that the South Asian monsoon system has been studied extensively, relevant past studies on the Indian summer monsoon are summarized to provide background for investigating the large-scale monsoon variability over the Horn of Africa.

Many authors have shown that the South Asian monsoon system exhibits large variability on intraseasonal, interannual, and interdecadal timescales (Negal et al. 1995; Webster et al. 1998; Vernekar and Ji 1999; Wu et al. 1999; Krishnamurthy and Shukla 2000; Clark et al. 2000; Gadgil 2000; Krishnamurthy and Goswami 2000; Lawrence and Webster 2002). The prominent features of the monsoon variability at different time-scales are summarized next.

#### 2.3.1 Intraseasonal variability

On intraseasonal time-scales, the most dominant fluctuations in the monsoon are active/break cycles with quasi periods of 10-20 days and 30-60 days (Sikka and Gadgil 1980; Singh et al. 1992; Vernekar and Ji 1999; Wu et al. 1999; Gadgil 2000; Annamalai and Slingo 2001). These intraseasonal fluctuations have been linked to the Madden-Julian Oscillation (Webster et al. 1998; Annamalai and Slingo 2001; Lawrence and Webster 2002; Hsu et al. 2004), or are thought to be manifestations of the variability in monsoon disturbances and components of the monsoon system (Krishnamurti and Ardunai 1980; Krishnamurthy and Shukla 2000). The Madden-Julian Oscillation (MJO; Madden and Julian 1971) is a low frequency (30-60 day period) oscillation in the tropical large-scale circulation, which generally is manifest as an eastward propagating, equatorially trapped baroclinic oscillation in the upper tropospheric wind and cloud/rainfall fields (Webster et al. 1998). The oscillation appears to have a larger amplitude over the Indian and western Pacific Oceans, where it strongly interacts with or modulates deep convection and influences the monsoon onset and activity over a large area (Chakraborty and Krishnamurti 2003).

Using satellite observations, Sikka and Gadgil (1980) noted a 2-6 week oscillation in convection bands associated with the maritime and continental ITCZ during the transition seasons as well as the peak of the monsoon season and linked these oscillations with the onset, withdrawal, and active/break cycles of the monsoon. Krishnamurti and Bhalme (1976) also noted very pronounced quasi-biweekly oscillations in rainfall, surface pressure, the cross-equatorial LLJ, and monsoon cloudiness. These oscillations do not change the character of the mean monsoon flow, but strengthen or weaken the entire system (Krishnamurthy and Shukla 2000). During break monsoon, sea level pressure increases over northwest India and the monsoon trough moves northward to the foothills of the Himalayas. This creates below normal rainfall over central India and above normal rainfall over the foothills of the Himalayas (Vernekar and Ji 1999), and is accompanied by lower tropospheric weak westerlies (easterlies) north (south) of the equator (Krishnamurthy and Shukla 2000).

The active and break cycles of the Indian monsoon also are linked to the Southern Hemisphere subtropical anticyclones. Based on results of modeling studies, Rodwell (1997) suggested that Southern Hemisphere midlatitude weather systems could trigger breaks in the Indian monsoon rainfall by injecting dry, high negative potential vorticity air into the low-level monsoon flow. Because the Ertel potential vorticity is conserved by air parcel in the absence of friction and heat sources, Rodwell (1997) indicated that the Findlater Jet transports not only moisture, but also negative potential vorticity from the Southern Hemisphere into the Northern Hemisphere. The author further argued that as the Southern Hemisphere subtropical anticyclones pass over the eastern coast of South Africa, the southeasterly winds from northern Madagascar toward

the east coast of Africa and the LLJ across the Arabian Sea are strengthened. At the same time, the air in the eastern flank of the anticyclone crosses the equator maintaining its strong negative potential vorticity signature. With substantial negative potential vorticity north of the equator, the flow over the Arabian Sea becomes more diffluent and turns southward, reducing the low-level inflow into India. Furthermore, the air crossing the equator from the Southern Hemisphere is likely to retain its dry characteristics because the air may not have enough time for a sustained moistening from the underlying ocean surface. Rodwell (1997) concluded that the immediate increase of rainfall over India corresponding to a surge in the cross-equatorial LLJ may not be the dominant effect of the passage of a ridge in the Southern Hemisphere midlatitudes. The model study indicates that the rainfall over central and northeastern India could subsequently fall by as much as 40% averaged over an 8-day period in response to a midlatitude injection of air into the low-level monsoon inflow, with a corresponding 50% increase in rainfall over the southern tip of the Indian Peninsula (Rodwell 1997). These rainfall patterns are consistent with the conditions that prevail during break monsoon.

#### 2.3.2 Interannual variability

Monsoon variability is governed by slowly varying surface boundary conditions such as SSTs, surface albedo, and soil moisture (e.g., Charney and Shukla 1981; Kawamura 1998). The southwest monsoon exhibits biennial and multi-year variability associated with the Tropospheric Biennial Oscillation and the El Niño-Southern Oscillation (ENSO) phenomena (Terray 1995; Meehl 1997; Webster et al. 1998, Clark et al. 2000). These modes of variability next are discussed separately.

#### (a) Biennial variability

The Tropospheric Biennial Oscillation (TBO) is the tendency for a strong monsoon to be followed by a weak monsoon and vice versa (Meehl et al. 2002), and appears to be a fundamental characteristic of the Asian/Australian monsoon occurring with an irregular period of 2-3 years (Webster et al. 1998; Chang and Li 2000). Its existence is explained as arising from coupled interactions in the landatmosphere-ocean system over the monsoon regions involving SST-monsoon, monsoon-Walker circulation, evaporation-wind, and wind stress-ocean thermocline feedbacks (Brier 1978; Meehl 1997; Webster et al. 1998; Chang and Li 2000; Meehl and Arblaster 2002, Wu and Kirtman 2004). A fundamental element of the TBO is the large-scale east-west atmospheric circulation that links anomalous convection and precipitation, winds, and ocean dynamics across the Indian and Pacific sectors (Chang and Li 2000; Meehl et al. 2003). This circulation connects convection over the Asian-Australian monsoon regions both to the central and eastern Pacific (the eastern Walker cell), and to the central and western Indian Ocean (the western Walker cell), and provides the low-level anomalous moisture convergence (divergence) that preconditions the

atmosphere for a wet (dry) monsoon (e.g., Meehl et al. 2003; Wu and Kirtman 2004). Using observed upper-ocean data for the Indian Ocean, Meehl et al. (2003) noted that slowly eastward-propagating equatorial ocean heat content anomalies, westward-propagating ocean Rossby waves south of the equator, and anomalous cross-equatorial ocean heat transports contribute to the heat content anomalies in the Indian Ocean and thus to the ocean memory and consequent SST anomalies. Furthermore, a combination of tropical convective heating anomalies over East Africa, Southeast Asia, and the western Pacific produces a Rossby wave-type response that alters the seasonal midlatitude circulation, and subsequently the land-sea meridional tropospheric temperature contrast (Meehl 1997; Wu and Kirtman 2004). For example, an anomalous ridge over Asia during northern winter weakens the midlatitude westerlies, and creates warmer and drier conditions that lead to decreased snow cover over Asia. The anomalously warm south Asian landmass favors an enhanced land-sea temperature contrast and contributes to a strong monsoon.

The specific processes that lead to the biennial oscillation described in the literature cited above can be summarized as follows. Warm SST anomalies over the Indian Ocean increase lower-tropospheric moisture through enhanced surface evaporation. As the South Asian monsoon develops, the excess moisture is advected into South Asia by southwesterly winds. This intensifies the convective rainfall there and leads to a strong monsoon. On the other hand, due

to the stronger surface winds and enhanced evaporation and mixing, the Indian Ocean progressively cools, and by the end of the monsoon season, negative SST anomalies are established. The ocean retains the cool conditions until a year later, when the convective maximum associated with the seasonal cycle again arrives. The convective heating associated with the stronger monsoon also intensifies a planetary-scale east-west circulation, leading to anomalous easterlies over the western and central Pacific. These anomalous easterly winds raise (deepen) the thermocline in the eastern (western) Pacific. The shallow thermocline, maintained by westward flowing surface current, deeper eastward undercurrent, upwelling, and surface divergence in the eastern Pacific (e.g., Trenberth 1991, p. 19), sustains cooler SSTs in the east. The east-west SST gradient further intensifies the anomalous easterlies over the central Pacific, reinforcing the tilting of the thermocline and the warming of the western Pacific waters. This pattern further strengthens the Walker cells and sets up the conditions for stronger Australian Monsoon. In addition, the warming of the western Pacific induces a stronger local Walker cell and hence a surface westerly anomaly over the Indian Ocean. This anomalous westerly wind helps the negative SST anomalies over the Indian Ocean to persist through the succeeding seasons, leading to a weaker South Asian monsoon the following summer. Furthermore, a weak (strong) tropospheric meridional land-sea temperature contrast contributes to a weak (strong) South Asian monsoon. The chain of events in the weak monsoon phase is a mirror image of the sequence of developments described above.

The temporal asymmetry of the TBO is demonstrated by the lagged correlations between the Indian monsoon and SSTs over the western and eastern Pacific Ocean (Fig. 2.2, from Yasunari 1990). The lag correlation magnitudes gradually increase after the summer monsoon season and reach maxima in the following boreal winter (Fig. 2.2). The correlations have the opposite sign for the eastern and western Pacific Ocean. Although the correlation magnitudes for western Pacific Ocean of the preceding year are less strong, a similar lag



FIGURE 2.2. Lagged correlations between the Indian monsoon rainfall anomaly and the SST anomaly in the western Pacific Ocean (0°-8°N, 130°-150°E; solid curve) and the eastern Pacific Ocean (0°-8°N, 170°-150°W; dashed curve). Y(-1) and Y(+1) refer to the year before and after reference year (Y0). The statistical significance at the 95% and 99% levels are shown by horizontal lines. From Yasunari (1990).

correlation pattern was found for East Asian summer monsoon rainfall (Shen and Lau 1995; not shown). In both cases, strong (weak) summer monsoon tends to lead a La Niña (El Niño) in the equatorial Pacific in the later seasons of the year (Webster et al. 1998). This suggests that anomalous convective heating associated with the Asian summer monsoon may play an active role in forming or triggering anomalous SST in the equatorial Pacific by altering the large-scale east-west circulation through processes involving monsoon-SST, evaporationwind, and wind stress-ocean thermocline feedbacks (Webster et al. 1998; Chang and Li 2000).

#### (b) The El Niño Southern Oscillation mode

Most of the interannual variability in the south Asian/Indian monsoon system is linked to the lower frequency mode of variability associated with ENSO (Terray and Dominiak 1995; Annamalai et al. 2005). The largest SST anomalies covering a considerable region occur mainly in the central Pacific Ocean associated with the ENSO phenomenon and explain a substantial fraction of monsoon rainfall variance (Kawamura 1989; Vernekar and Ji 1999). Modeling experiments also provided supporting evidence that ENSO is the dominant source of monsoon variability. Based on results from a set of 90-day model integrations forced by a variety of specified SSTs, Palmer et al. (1992) asserted that the remote effect of El Niño is much more important in determining the interannual variability of the Asian monsoon, while the monsoon system's response to Atlantic and Indian Ocean SST forcing is weak and localized.

The interaction between ENSO and the Asian summer monsoon, however, is complex and long has been the focus of many studies (Ropelewski and Halpert 1987; Ju and Slingo 1995; Webster et al. 1998; Chakraborty and Krishnamurti 2003). Ju and Slingo (1995) argued that the main influence of ENSO on the Asian summer monsoon appears to be associated with the latitudinal position and strength of the tropical convective maximum over Indonesia and the west Pacific in the preceding spring, and suggested that changes in large-scale circulation patterns associated with the equatorial Pacific SST anomalies in the preceding boreal winter or spring could be responsible. These changes are either driven remotely through teleconnections or locally by anomalous heating. Developing this hypothesis further using additional modeling case studies, Soman and Slingo (1997) showed that the modulation of the Walker circulation is the dominant mechanism responsible for a weakened Asian monsoon during El Niño years. Vernekar and Ji (1999) also noted that positive SST anomalies shift the heavy precipitation region from the extreme western Pacific to the central Pacific Ocean and create an anomalous heat source in the atmosphere that modulates the large-scale circulation and the normal mode of the Walker circulation. The shift in the climatological Walker circulation results in enhanced low-level convergence over the equatorial Indian Ocean and drives an anomalous Hadley circulation with descent and decreased monsoon rainfall over the Indian continent (Krishnamurthy and Goswami 2000; Clark et al. 2000).

On the other hand, Ju and Slingo (1995) noted that the modulation of the Walker circulation in La Niña years was not very strong and therefore may not be a dominant mechanism for determining the strength of the monsoon over South Asia. Through model sensitivity experiments, Soman and Slingo (1997) noted that although the Walker circulation is indeed modified for La Niña experiments, there is very little modulation of the divergent circulation over the monsoon regions compared with the results for El Niño experiments. Soman and Slingo (1997) concluded that the modulation of the local Hadley circulation over the warm-pool region could be a dominant factor in determining the behavior of the tropical convective maximum and therefore the strength of the monsoon over India and Southeast Asia during La Niña years. They further noted that the enhancement of the tropical convective maximum over the western Pacific during La Niña could arise from an increased zonal SST gradient as well as from in situ warm SST anomalies.

## 2.3.3 Interdecadal variability

In recent decades the inverse relationship between Indian monsoon rainfall and ENSO has considerably changed (Chakraborty and Krishnamurti 2003; Wu and Kirtman 2004) probably because of additional forcing associated with

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monsoon internal variability (Krishnamurthy and Goswami 2000). Kumar (1999) noted a weakening in the ENSO-monsoon relationship after the 1976-77 climate shift (Nitta and Yamada 1989; Trenberth and Hurrell 1994; Graham 1994), following which the amplitude, spatial structure, and temporal evolution of El Niño events have changed significantly (Trenberth 1990; Wang 1995; Terray and Dominiak 2005). The 1976-77 climate shift, also known as regime change, refers to a sudden change associated with the decadal scale variability in atmospheric and oceanic states (e.g., Terray and Dominiak 2005). The changes in ENSO properties occurred concurrently with the Pacific decadal climate fluctuations and are indicative of a strong link between the interdecadal fluctuation in the North Pacific climate and the interannual and interdecadal climate variations over the tropical Pacific and Indian Ocean (Terray 1995; Zhang et al. 1997). Furthermore, Zhang et al. (1997) showed the structure of the interdecadal variability of the monsoon to be very similar to the interannual ENSO mode.

Many studies have documented the variability of Indian monsoon and its link to the ENSO cycle on the interdecadal timescale (Webster et al. 1998; Torrence and Webster 1999; Krishnamurthy and Goswami 2000; Clark et al. 2000). Using observed and reanalysis data, Krishnamurthy and Goswami (2000) found a strong correlation between the Indian monsoon rainfall and ENSO on the interdecadal timescale. In addition, they showed that the spatial patterns of SST and sea level pressure (SLP) associated with the interdecadal variations of Indian monsoon rainfall are nearly identical to those associated with the interdecadal variations of ENSO indices and demonstrated that the interdecadal variation of the Indian summer monsoon and that of the tropical SST are parts of a tropical coupled ocean-atmosphere mode. In particular, they showed that the regional Hadley circulation and Walker circulation anomalies associated with the strong (weak) phases of the interdecadal oscillation are similar to those associated with the strong (weak) phases of the interdecadal oscillation are similar to those associated with the strong (weak) phases of the interdecadal oscillation are similar to those associated with the strong (weak) phases of the interdecadal oscillation are similar to those associated with the strong (weak) phases of the interannual variability over a considerable part of the equatorial region.

### 2.3.4 The Indian Ocean and ENSO

In addition to the Pacific Ocean, the Indian Ocean also experienced a sudden surface warming in the mid 1970s (Nitta and Yamada 1989; Clark et al. 2000; Terray and Dominiak 2005). Associated with this warming, the correlation structure between Indian Ocean SST and the Indian monsoon rainfall and ENSO cycle has significantly changed (Clark et al. 2000; Terray and Dominiak 2005). To determine the Indian and Pacific Oceans' SST variability related to ENSO events before and after 1976-77 climate shift, Terray and Dominiak (2005) correlated 2month average SST over southeast Indian ocean with December-January average Niño-3.4 (5S-5N,170-120W) SST time series for the two periods at different lag times. The result clearly shows that the ENSO behaves differently before and after 1976-77 regime change. One of the salient features of the decadal fluctuation is the notable difference in the evolution of Indian Ocean SST anomalies associated with ENSO for the pre- and post-1976-77 periods.

Before the 1976-77 climate shift, significant positive correlations first appear over the North Arabian Sea during the late Indian summer monsoon and expand through the following seasons. During the mature phase of El Niño (La Niña), the whole Indian Ocean became significantly warmer (colder). After the 1976-77 regime shift, El Niño onsets were preceded by a basin-wide cooling over the Indian Ocean with strong negative anomalies over southeastern Indian Ocean through early summer. Weaker positive SST anomalies appear over the western and northern Arabian Sea late in summer and continue through fall, with an emergence of а Tropical Indian Ocean dipole that maximizes in October/November. The term dipole is used to describe an east-west SST anomaly contrast over the tropical Indian Ocean, and is thought to have caused excessive rain and flooding over equatorial eastern Africa and the Nile as early as 1961(e.g., Saji et al. 1999). There is, however, much controversy and uncertainty in the scientific community about the nature and development of this supposed dipole, and its independence from the ENSO (Webster et al. 1999; Hastenrath 2003; Yamagata et al. 2003). In particular, noting his findings of the close association between zonal SST gradient, equatorial westerlies, East African Rainfall, and the Southern Oscillation in his earlier studies, Hastenrath (2002,

2003) concluded that there is no SST seesaw between the eastern and western equatorial Indian Ocean and argued against a misleading use of the term dipole.

Although previous studies (Palmer et al. 1992; Nagai et al. 1995) suggested that the role of the Indian Ocean SST in ENSO or the atmospheric response to the Indian Ocean SST anomalies forcing is weak, Terray and Dominiak (2005) argued that this was true before the 1976-77 climate shift but not afterwards. In particular, the evolution of Indian Ocean SST during the initiation and development of ENSO led Terray and Dominiak (2005) to assert that the Indian Ocean plays an active role in the transition phases of ENSO and strengthens the seasonal positive wind-evaporation-SST feedback over the southeast Indian Ocean. They speculate further that the spatial extension of the Indian Ocean warm pool may explain the stronger links between southern Indian Ocean variability in boreal winter and the ENSO evolution observed after the 1976-77 regime shift.

#### 2.3.5 Large-scale variability over the Horn of Africa

As indicated in previous studies (Camberlin 1997; Vizy and Cook 2003), there are many common features in rainfall variability over India and the Horn of Africa. In a recent comprehensive observational study on Ethiopia, Segele and Lamb (2005) discussed key characteristics of the summer rains of Ethiopia and showed that there is considerable variability in the onset and cessation of the June-September rains (Kiremt). On intraseasonal timescales, the Kiremt season is interspersed with weak rainfall periods or dry-spells that last from a few days to weeks. These "breaks" in the rainfall are excessively frequent and long during typical drought years. Based on upper air analysis for Addis Ababa (9.2°N, 38.5°E), it was shown that long dry spells are characterized by the absence of surface southwesterlies, an abnormally warm and dry lower troposphere, and weakened 500-100 hPa layer dynamics as evidenced by unusually low geopotential heights and a slow TEJ. It was found also that most of the long dry spells tend to occur during the last phases of the season.

On the interannual timescale, Segele and Lamb (2005) linked the Ethiopian Kiremt to the ENSO phenomenon in some respects. Spatially coherent and statistically significant correlation coefficients were identified between Kiremt rainfall/onset/growing length and sea surface temperatures over much of the equatorial Pacific Ocean. The start of the rain often is delayed during El Niño with the magnitude of correlation coefficient between monsoon onset over Ethiopia and SSTs over much of central and eastern Pacific Ocean exceeding 0.45. The growing length is even more strongly negatively correlated with SSTs over the equatorial Pacific, with the magnitude of correlation exceeding 0.55 over the central Pacific Ocean, which indicates shorter growing length and drier conditions during the warm ENSO phase. Interestingly, the summer rainfall retreat is more strongly correlated with Indian Ocean SST, with strong positive

correlation values (> +0.45) over the western Indian Ocean. Although not quite strong and widespread as the correlation patterns for the equatorial Pacific Ocean, Segele and Lamb (2005) also found a moderate (0.35–0.4) positive correlation between Kiremt onset and western Indian Ocean SST anomalies.

# 2.3.6 ENSO, Indian Ocean SSTs, and rainfall variability over the Horn of Africa

The above summary indicates that rainfall variability on the interannual time scale over the Horn of Africa is related in part to ENSO variability and SST variability over the Indian Ocean. However, the relative importance of ENSO and non-ENSO-related SST patterns for eastern Africa rainfall seems to be region/season dependent or unclear, and warrants further investigation over the Horn of Africa. For instance, Barnston et al. (1996) suggest that non-ENSOrelated SST patterns influence African rainfall anomalies with equal or greater strength than ENSO. Other studies (Latif et al. 1999; Sun et al. 1999) also indicate that SSTs over Indian Ocean drive east African rainfall and emphasized that ENSO-related SST anomalies are not directly involved. Moreover, Goddard and Graham (1999) observed the prominent role Indian Ocean SST plays in producing an observed African rainfall dipole pattern (rainfall anomalies of opposing sign in central-east and southern Africa) and its contribution to rainfall variability over eastern and southern Africa. They further stated that "While the SST variability of the tropical Pacific exerts some influence over the African

region, it is the atmospheric response to the Indian Ocean variability that is essential for simulating the correct rainfall response over eastern, central, and southern Africa". (p. 19,099)

The aforementioned studies indicate an apparent contradiction concerning the influence of the Indian Ocean on African rainfall. On one hand, Segele and Lamb (2005) found only modest effects of Indian Ocean SSTs on Ethiopian summer rainfall onset and cessation. On the other hand, many other studies reported stronger effects of Indian Ocean SSTs on African rainfall variability more generally. This study attempts to identify clearly the effects of Indian Ocean SSTs on the Horn of Africa rainfall. Specifically, could the effects of the Indian Ocean be more pronounced within the summer, but not during the onset and cessation of Ethiopian summer season? Or is it possible that the results of Barnston et al. (1996), Latif et al. (1999), Sun et al. (1999), and Goddard and Graham (1999) are valid only for other regions of eastern and southern Africa? To address these and other pertinent issues, detailed observational analysis and modeling studies will be performed for the Horn of Africa.

Most of the studies reviewed earlier in this chapter are related primarily to the Indian monsoon rainfall, and quite a few are directly associated with rainfall variability over the Horn of Africa. This points to an incomplete understanding of the mechanisms associated with (especially) Ethiopian rainfall variability. On the interannual time scale, for example, correlation analyses have indicated a strong link between SSTs over the tropical oceans and Ethiopian rainfall (e.g., Gissila et al. 2004; Segele and Lamb 2005; Korecha and Barnston 2006). However, there have not been studies that attempted to explain the physical mechanisms involved in that link other than ascribing it loosely to interactions between the equatorial Walker circulation and a regional Hadley circulation (section 2.3.2). This situation motivated the present research to address, for the first time, the following key questions:

- How does such interaction manifest in the local circulation to affect rainfall over the Horn of Africa?
- How do remote teleconnections change the regional circulations?
- How do the regional circulations during ENSO compare with the normal circulation features?

Segele and Lamb (2005) for the first time examined the tropospheric responses associated with the basic characteristics of the main rainy seasons of Ethiopia using local upper air data for one station and provided valuable insight into the regional circulation changes accompanying selected "wet" and "dry" summers. However, to fully address the issues raised above and explore the mechanisms involved, detailed analyses of high-resolution local and regional scale flows need to be performed. In addition, since ENSO explains up to only about 30% of the interannual rainfall variability, the bulk of rainfall variance over

the Horn of Africa must be explained by processes linked to other internal and external controls.

One of the tools employed in this study is a regional climate model. The Abdus Salam International Center for Theoretical Physics (ICTP) REGional Climate Model version 3 (RegCM3) will be used to simulate the evolution of the Horn of Africa monsoon for 1982-99. In addition, the RegCM3 will be used to investigate the dynamical influence of the Indian Ocean and the effects of local surface properties on summer rainfall. Pertinent regional climate model studies and related outstanding issues therefore are discussed in the next section.

# 2.4 Regional Climate Model

### 2.4.1 Overview

Regional climate models increasingly have been utilized to study mesoscale climate patterns and processes (Small et al. 1999; Pal et al. 2005) and regional climate variability (Sun et al. 1999; Wang et al. 2003) over different parts of the world. Regional climate models (RCMs) are useful tools for studying regional climate variability at different timescales and understanding the role that mesoscale and regional scale climate processes play in shaping the atmospheric response to external forcing (Diffenbaugh and Sloan 2004).

Typically, RCMs are initialized and run over limited-area domains and driven at the lateral boundaries by time-dependent large-scale meteorological fields obtained either from analyses of observations or general circulation model (GCM) simulations (Seth and Giorgi 1998; Giorgi and Bi 2000). Because the lateral boundary conditions (LBCs) limit the degrees of freedom of the model, the climatology obtained from a properly configured RCM will not strongly diverge from the forcing fields (Giorgi and Bi 2000) and thus RCMs can provide long simulation results from multi-year to multi-decadal and longer timescales. Model solutions in the interior of the domain are determined by a dynamical equilibrium resulting from nonlinear interactions among large-scale forcing, model generated forcing in the interior of the domain (e.g., topography), and the internal model physics and dynamics (Anthes et al. 1989; Seth and Giorgi 1998; Giorgi and Bi 2000), and likely capture regional patterns of precipitation, temperature and soil hydrology induced by local topography, land-cover patterns, and soil hydrology (Semazzi et al. 1993; Lee and Suh 2000). Thus, carefully designed and configured RCMs are capable of describing climate feedback mechanisms acting at the regional scale and can provide high resolution (10 to 20 km or less) and multi-decadal simulations (Houghton et al. 2001).

As noted by Houghton et al. (2001), the use of RCMs for climate application was pioneered by Dickinson et al. (1989) and Giorgi (1990). In their pioneering works on the use of a nested limited area model (LAM) for climate studies, Dickinson et al (1989) and Giorgi et al. (1989) nested a limited area model in a General Circulation Model to simulate regional precipitation climatology over the mountains of western United Sates. In the nesting procedure, the GCM output is used to provide the initial and lateral atmospheric boundary conditions necessary to drive/constrain the LAM. The nested model system produced better regional climatic details than the large-scale circulation and compared well with high resolution observations, particularly in their spatial distribution. Over the years, RCMs have been applied to a wide variety of studies ranging from climate and surface hydrologic processes and sensitivity studies to simulations of present, past, and future climates on the mesoscale and regional scale (Giorgi 1991; Giorgi and Bi 2000, Pal et al. 2005).

While improvements made over the years lowered the bias between modeled and observed precipitation (Giorgi et al. 1993), RCMs tend to overestimate precipitation frequency and the number of light precipitation events (Mearns 1995; Giorgi and Marinucci 1996) and produce large bias over mountainous regions (Giorgi and Shields 1999). Results of a sensitivity study by Giorgi and Marinucci (1996) especially show that model sensitivity to convection parameterization is of the same order of, or greater than, the sensitivity to topography and horizontal resolution during summer even in highly mountainous regions. Moreover, Giorgi and Shields (1999) and Pal et al. (2005)

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stressed that the use of different convection schemes significantly affects simulated precipitation and leads to substantially different simulations of lower tropospheric circulations.

### 2.4.2 Simulation of Intraseasonal and Interannual Variability

Regional climate models have been used to investigate the intraseasonal and interannual rainfall variability over Africa (e.g., Semazzi et al. 1993; Sun et al. 1999a, 1999b), east and south Asia (e.g., Bhaskaran et al. 1998; Small et al. 1999; Lee and Suh 2000), Europe (e.g., Giorgi et al. 1993c; Lüthi et al. 1996; Halenka et al. 2006), and the continental USA (e.g., Giorgi et al. 1996; Dai et al. 1999; Giorgi and Shields 1999). In general, the RCMs are reported to have performed well, especially on the intraseasonal and interannual time-scales. However, Dai et al. (1999) found a significant discrepancy between the modeled and observed diurnal cycles of precipitation over the United Sates when simulating 1993 summer precipitation using RegCM.

Over the Indian monsoon region, Bhaskaran et al. (1998) showed that the leading mode of sub-seasonal variability of the South Asia monsoon, a 30 to 50 day oscillation of circulation and precipitation anomalies, was more realistically captured by an RCM than the driving GCM. The fine-resolution nested RCM leads to the identification of important spatial details not present in the GCM distributions especially in mountainous regions. For example, the RCM simulates a strong precipitation signal, which appears to represent an orographic component of the response to circulation anomalies associated with the intraseasonal oscillation, but this precipitation signal largely is absent in the GCM simulation. Results of regional model simulations by Vernekar and Ji (1999) relate the active and break Indian monsoon conditions to the phase of the regional Hadley circulation associated with the strength of the South Asian continental ITCZ in the monsoon trough and the oceanic ITCZ in the equatorial Indian Ocean. In the positive phase, there is ascending motion in the continental ITCZ and descending motion in the oceanic ITCZ. In the negative phase, a descending branch over the continent suppresses convective activity. This overturning sometimes lasts a few days leading to break and active monsoon cycles.

Over Sahelian West Africa, Semazzi et al. (1993) nested a high resolution atmospheric model (MM4) within the NCAR Climate Community Model version 1 (CCM1) to investigate the sensitivity of the climate over the region to largescale circulation anomalies corresponding to dry (1984) and wet (1950) summers. The authors used observed global SSTs for 1950 and 1984 to prescribe the lower boundary conditions. The nested simulation showed significant improvement over the GCM results and produced centers of precipitation maxima in good agreement with observed patterns for both years. Moreover, Semazzi et al. (1993) noted that consistent with the observational diagnostic results of Lamb and Peppler (1991), the southwesterly surface monsoon flow for the simulated dry year did not extend as far north along the West African coast as for the simulated wet year. The improvement in the nested model simulation presumably is a direct reflection of detailed representation of topography, land-sea contrasts, and land surface processes.

For East Africa, comprising Kenya, Tanzania, and parts of the Democratic Republic of Congo, Sun et al. (1999a) customized the NCAR Regional Climate version 2 (RegCM2) and investigated the physical mechanisms that govern the October-December short rains over the region. The European Center for Medium-Range Weather Forecasts (ECMWF) global reanalysis data were used to generate the initial and LBC for RegCM2. They reported that the RCM simulated the large-scale circulation features, as well as prominent local features like the Turkana low-level jet and lake/land breeze circulation. Although the model overall showed good agreement with observations in capturing major precipitation maxima, areas of negative rainfall bias were identified over the tropical forest regions. In addition, the authors found that the large-scale circulation anomalies play the most important role in shaping the precipitation anomalies. Sun et al (1999b) later applied the customized RegCM2 to study the interannual rainfall variability of the region for 1982-93 and found that the model reproduced the interannual variability of precipitation, although there were certain discrepancies in some years.

### 2.4.3 Impacts of Land-Surface Characteristics

Investigation of the impacts of land surface characteristics on the atmosphere is relevant to the current study for the Horn of Africa. As indicated earlier, the 1984 summer was the driest season for Ethiopia since at least 1961 (Segele and Lamb 2005). The drought conditions were exacerbated by the total failure of the short rains during the preceding spring, especially over northeastern regions. The dry conditions likely reduced the vegetation coverage on a large-scale over northern Ethiopia. It is, therefore, of great scientific interest to explore the relevance of the reduced vegetation coverage on the following summer using a regional climate model.

Land surface characteristics such as soil moisture, surface albedo, and vegetation cover can have substantial impacts on atmospheric circulations and local climate patterns by affecting fluxes of heat, momentum, and water substances (Copeland et al. 1996; Small 2001). Based on mesoscale model simulation results, Crawford et al. (2001) report that soil moisture and the coverage and thickness of green vegetation have large effects on the magnitudes of surface sensible and latent heat fluxes. Substantial gradients in sensible heating resulting from contrasts in vegetation cover can modify existing mesoscale circulations or can result in the onset of thermally induced sea-breezelike circulations, also known as land or vegetation breezes, that may trigger convection and lead to severe weather (Anthes 1984; Segal et al. 1989; Clark and Arritt 1995). Furthermore, regional contrasts in evapotranspiration and surface heating, resulting from differences in land surface characteristics between adjacent areas, may also significantly alter regional temperature and rainfall patterns (Pielke 1991).

Douville et al. (2001) investigated the relevance of soil moisture for simulating the Asian and African monsoons using the Action de Recherche Petit Echelle Grande Echelle (ARPEGE) global climate model. The soil moisture conditions are specified over a limited domain that covers 10°-20°N, 20°W-40°E for the Asian and 5°-25°N, 60°-120°E for the African monsoons. Soil moisture conditions vary freely within a predefined domain over Asia or Sudan-Sahel region separately, but the soil moisture constraints gradually disappear in a 5° buffer zone surrounding the control domain. Sensitivity experiments were performed for idealized cases in which soil moisture in each region was limited by the value at the wilting point or at the field capacity but relaxed to the freerunning soil moisture values within the buffer zone. The simulations used the Global Soil Wetness Project (GSWP) soil moisture climatology for 1987 and 1988. These simulation results then were compared with a control simulation with free-running soil moisture determined by the Interactions between Soil Biosphere and Atmosphere (ISBA) land scheme but relaxed to GSWP soil moisture climatology for 1987 and 1988. To detect the soil moisture signal against the internal atmospheric variability, ensembles of seasonal simulations using the

same climatological SSTs but different initial conditions were analyzed. The results of the simulation show different sensitivity for the Indian and Sudan-Sahel regions. The most important difference is that African rainfall increases with increasing soil moisture but Indian subcontinent precipitation does not show a clear response. Douville et al. (2001) suggest that this contrast is partly related to the more dynamical and chaotic nature of the Asian monsoon, for which moisture convergence is about 2 times that found over Sudan-Sahel so that water cycling has a weaker influence on seasonal rainfall.

Later, Douville (2002) extended the previous study to investigate the relevance of soil moisture for simulating the interannual climate variability for 1987 and 1988 over the Sudan-Sahel and Asia using realistic SSTs and soil moisture. The GCM simulations further indicated that the influence of soil moisture was stronger over the Sudan-Sahel region and weak and less coherent over Asia. In fact, the simulations showed that the variation of the Asian monsoon between 1987 and 1988 were mainly driven by SST anomalies. Thus, realistic SST and soil moisture boundary conditions are needed to simulate correctly Sahelian rainfall variability. The positive soil moisture feedback over the Sudan-Sahel region compares well with the findings of Small (2001) in which wet soil in the North America Monsoon region enhances summer precipitation within the area.

Based on ground observation, Wendler and Eaton (1983) noted that over bare soil, surface temperatures increase when albedo declines but found the opposite for vegetated areas. Using results of RCM sensitivity studies, Copeland et al. (1996) confirmed that albedo changes lead to changes in net radiation available at the surface, but it is the partitioning of this energy between latent and sensible flux due to vegetation characteristics like leaf area index and fractional vegetation coverage that determine whether a region warms or cools. Based on RCM sensitivity results, Giorgi et al. (1996) highlighted the competing effects of sensible and latent heat fluxes on summer precipitation. As a positive feedback mechanism, simulations with wet soil conditions produced increases in evaporation, which provided additional atmospheric moisture favoring increased precipitation. On the other hand, simulations with reduced evaporation associated with dry soil conditions tend to increase buoyancy that dynamically sustains convection. However, Giorgi et al. (1996) noted that largescale circulations are more important in determining the overall precipitation anomalies than local effects associated with surface evaporation.

In a well known early study on Sahelian drought, Charney (1975) hypothesized that the reduction of vegetation increases surface albedo. This, in turn, induces subsidence and more radiative cooling of the air, which reduces convective activity and precipitation, and consequently vegetation. The reduction in precipitation is further enhanced by the decrease in

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evapotranspiration resulting from the depletion of vegetation. Using GCM simulation experiments, Charney et al. (1977) later showed that appreciable changes in albedo and evaporation rate significantly affect convective clouds and precipitation, especially in the semi-arid zones lying at the boundary between major deserts and adjacent monsoonal regions. In the presence of appreciable evaporation, the increase of albedo acts to reduce the absorption of solar radiation by the ground and therefore the transfer of sensible and latent heat into the atmosphere. The reduction in convective clouds allows more solar radiation to reach the ground, but it reduces the downward flux of longwave radiation more strongly, so the net radiation absorbed by the ground is reduced. Charney et al (1977) concluded that with or without evaporation, the increase in albedo causes a net decrease of radiative flux into the ground and therefore a net decrease of convective clouds and precipitation. Picon (1986) also applied a GCM to study the effects of albedo on Sahel climate and obtained lower precipitation rates, reduced net solar radiative flux, and decreased evaporation rates when surface albedo was increased over the Sahel.

Using a more realistic representation of the changes in land surface characteristics, Xue and Shukla (1993, 1996) further explored the link between land surface conditions and atmospheric circulation for the Sahel through highresolution GCM sensitivity experiments. To represent the current desertification in the Sahel, Xue and Shukla (1993) changed model vegetation types for the region 10°-18°N to reflect desert-like land surface conditions. The authors indicated that this representation of land surface changes is more realistic compared to most previous sensitivity studies that specify somewhat arbitrary values of albedo or soil moisture. The simulation results of Xue and Shukla (1993) showed that the Sahel rainfall was reduced due to desertification and the rainy season was delayed almost by half a month. The desertification experiment also revealed a weak southwesterly moisture flow, reduced moisture convergence, decreased evaporation rate, and a southward shift in the axis of maximum rainfall. In their follow-up study, Xue and Shukla (1996) investigated the effects of large-scale afforestation on the sub-Saharan region by replacing shrubs and bare soils with broadleaf trees in the GCM experiments. The results showed that the rainfall is augmented in most afforestation areas but reduced to the south of those areas. In contrast to the desertification experiment, the model responded much more slowly to the land surface changes in the afforestation experiment, indicating nonlinear effects of land surface characteristics. In addition, Xue and Shukla (1996) noted that afforestation has the largest impact for a dry-year simulation.

Given the impact of soil moisture, albedo, and vegetation on rainfall discussed in this section, it is logical to assume that the failure of the 1984 Ethiopian spring rainfall and the depleted vegetation that could result from the dry conditions can affect the rainfall pattern the following summer. To assess the large-scale effects of the land surface changes in 1984, the basic methods of Xue and Shukla (1993, 1996) will be employed in our high-resolution model sensitivity investigation.

# 2.5 Scope of Proposed Work

A number of issues raised in the background discussion earlier indicate the lack of basic research and fundamental understanding on the Horn of Africa summer monsoon processes. Of major concern is the role of the Indian Ocean on the interannual rainfall variability. To examine the dynamical influence of the Indian Ocean and contribute toward the understanding of the physical mechanisms that govern the intraseasonal and interannual variability over the Horn of Africa monsoon, both observational and modeling studies will be conducted.

As a foundation for understanding the climate system over the Horn of Africa, a comprehensive observational study first will be conducted. The investigation utilizes raingauge and the NOAA Climate Prediction Center (CPC) Merged Analysis of Precipitation (CMAP) pentad data to identify the dominant modes of rainfall variability in the region. The large-scale circulation features corresponding to these modes then will be analyzed using the National Center for Environmental Prediction (NCEP) daily average Reanalysis data. The spacetime evolution of the individual physical modes associated with the Horn of Africa rainfall will be examined and the physical and dynamical linkage will be identified. This observational study will form the basis for the subsequent investigations on the predictability of summer rainfall. It also will help focus model sensitivity experiments that will be designed to study the effects of dry Ethiopian pre-monsoon seasons and SST variations over the Atlantic and the Indian Ocean on the Horn of Africa monsoon rainfall variability.

The domain of the rainfall variability study covers the region from 30-50°E and 5-20°N (Fig. 1.1). Since Ethiopia accounts for the largest portion of the domain and possesses all the climatic characteristics of the surrounding countries, Ethiopian raingauge stations can be assumed to represent the climate of the region adequately. While the study focuses on the main rainy season from June to September, it also uses daily and 5-day average time series for May-October, and monthly total rainfall time series for February-May, June-September, and January-December.

Building upon the results of the diagnostic analysis, the predictability of Ethiopian summer rainfall will be examined in detail. Using a novel prediction technique that combines wavelet analysis and linear regression, dependable and skillful empirical models are developed for forecasting Ethiopian rainfall at medium and long range time-scales. The applicability of the statistical prediction models will be discussed. For application of the regional climate model, the recently released RegCM3 will be comprehensively tested to examine its skill and select the best configuration and convective scheme that captures the region's climatic features. Although considerable improvements have been made in representing subgrid scale processes, recently Wang et al. (2003) reported low performance in precipitation simulation over the tropics due to the weak large-scale forcing and predominance of convection. Since most previous RCM studies have been applied to middle latitude regions (Sun et al. 1999a; Pal et al. 2005), it is imperative to perform exhaustive precipitation sensitivity tests to produce realistic regional precipitation patterns over tropical regions as convective precipitation still remains the most important sources of error in climate modeling (Sun et al. 1999a; Wang et al. 2003).

Model performance is evaluated by comparing simulated rainfall for known wet and dry summers with raingauge observations and satellite rainfall estimates. Once adapted and validated, the RegCM3 then will be applied over a sufficiently large domain that encompasses the major large-scale monsoon circulation systems to obtain a model simulated rainfall climatology and assess the interannual variability. For model initialization and LBCs, SST and the NCEP Reanalysis data were obtained from the NOAA-CIRES Climate Diagnostics Center (Boulder, Colorado; http://www.cdc.noaa.gov/). The RegCM3 also will be utilized to investigate the impacts of SST variations over the Atlantic and the Indian Ocean on rainfall over the Horn of Africa. The role of individual ocean basins and their relative importance to the Horn of Africa rainfall will be examined. Lastly, model sensitivity studies will be carried out to identify the effects of depleted vegetation that could result from weak spring rains on the amount and distribution of subsequent monsoonal rainfall over the Horn of Africa.

# CHAPTER 3: LARGE-SCALE CIRCULATION PATTERNS ASSOCIATED WITH DOMINANT MODES 0F MONSOON RAINFAL VARIABILITY DURING 1970-99: OBSERVATIONAL ANALYSES

## 3.1 Preamble

Recently, Washington et al. (2006) have highlighted the lack of systematic understanding of the basic state of the atmospheric circulation over critical parts of Africa. Furthermore, the authors noted that improvements in understanding the basic circulation patterns across Africa are essential for improving the management of activities affected by climate variability and future climate change, not only over Africa but also on a more global scale. This problem is particularly acute over the Horn of Africa, for which there never has been any basic research on the large-scale circulation patterns. Although the large-scale systems during the southwest Indian monsoon are generally associated with the Horn of Africa summer rainfall (e.g., Camberlin 1997; Segele and Lamb 2005), only a few comprehensive quantitative studies link those features specifically to local weather and climate patterns over the Horn of Africa. Segele and Lamb (2005) recently made a positive stride towards identifying the linkage between Ethiopian climate variability and the large-scale atmospheric circulation anomalies over Africa and the surrounding oceans for selected dry and wet Ethiopian monsoon seasons.

However, to understand weather and climate variability and develop physically based prediction models, it is important to understand the mechanisms involved and the large-scale circulation features associated with the region's rainfall variability. This chapter is dedicated to documenting and understanding the major modes of rainfall variability over the Horn of Africa and the associated large-scale atmospheric circulation patterns across Africa and the tropical Atlantic and Indian Oceans. This work will add to our knowledge of the basic regional circulation patterns and their association with/effects on the Horn of Africa rainfall. The study also enhances our understanding of the impacts of the global atmospheric and oceanic features on the Horn of Africa rainfall variability. In addition, the study lays the foundation for developing physically based prediction models on intraseasonal to seasonal time-scales by identifying dynamical/thermodynamic atmospheric and oceanic variables related to the major modes of rainfall variability during summer.

The first step in this study is identifying the major modes of rainfall variability over the Horn of Africa. This is achieved through the application of wavelet analysis to daily, 5-day, and monthly rainfall data. After identifying the frequency bands of the dominant modes of rainfall variability, both rainfall and several atmospheric and oceanic time series will be filtered identically for each frequency band. The filtered time series are subsequently analyzed using different statistical methods including, correlation, regression, and composite analyses.

## 3.2 Data and methodology

### 3.2.1 Data

The study utilizes several data sets. The first data set contains raingauge measurements for Ethiopia. Daily rainfall data for 121 Ethiopian stations were obtained on hard copy from the National Meteorological Services Agency of Ethiopia. As reported in Segele and Lamb (2005), these data were digitized and quality controlled to construct the first research quality rainfall data set for Ethiopia. Of the 121 stations obtained, 100 were determined to have their main rainy season during boreal summer and were used in this study. To supplement these raingauge data and to increase the spatial coverage over the Horn of Africa, Pentad CMAP rainfall estimates (Xie and Arkin 1997) were used. The CMAP data set is produced by a technique that produces pentad and monthly analyses of global precipitation in which observations from raingauges are merged with precipitation estimates from several satellite-based algorithms (infrared and microwave). The analyses are on a 2.5 x 2.5 degree latitude/longitude grid and extend back to 1979 (Xie et al. 1997). The data are available at ftp://ftpprd.ncep.noaa.gov/pub/precip/cmap.

For large-scale atmospheric circulation analyses, daily average products of the NCEP-NCAR reanalysis project were obtained from the NOAA-CIRES Climate Diagnostics Center (Boulder, Colorado; http://www.cdc.noaa.gov/). The daily averages include geopotential height, temperature, horizontal winds, vertical velocity, and specific humidity at standard pressure levels, and sea level pressure for the period 1970-99. The data are described by Kalnay et al. (1996). The period 1970-99 was chosen because a 30-yr analysis was considered sufficient to estimate the recent climatic characteristics of a region (e.g., Folland et al. 1991). Moreover, there are more reporting stations and fewer missing data in the Ethiopian raingauge data set after 1970 (e.g., Segele and Lamb 2005), and hence using data before 1970 may not give reliable results. To examine the connection between rainfall and sea surface temperature variability, the U.K. Meteorological Office Hadley Centre's global sea surface temperature (SST) data set, (HadISST1, Rayney et al. 2003) is utilized. The SST data set contains globally complete fields on an individual monthly basis for a 1° latitude-longitude grid from 1871 to present. For this study, however, only the 1970-99 data period is used.

### 3.2.2 Wavelet analysis

Wavelet analysis is a common tool for analyzing localized variations of power within a time series and reveals the temporal structure of nonstationary time series (Wang and Wang 1996; Torrence and Compo 1998). The technique is well suited to the study of multiscale, nonstationary time series that result from nonlinear interactions between several physical processes occurring within a broad set of temporal and spatial scales (Lau and Weng 1995; Webster and Hoyos 2004). Wavelet analysis is being used increasingly to decompose geophysical time series into time-frequency space to develop prediction models (e.g., Webster and Hoyos 2004; Mwale and Gan 2005) and detect periodicities and trends (e.g., Wang and Wang 1996; Baliunas et al. 1997; Chapa et al. 1998).

Geophysical time series often are nonstationary and contain combinations of various frequency regimes with contributions present throughout the entire temporal domain (Lau and Wang 1995; Webster and Hoyos 2004). The frequency regimes may be localized in time for a short period or may span a large portion of the data record. Localized events can be represented by a set of local parameters characterizing its frequency, intensity, time position, and duration. The time-integrated characteristics of these localized signals provide global information, which describes the temporal mean state (Lau and Wang 1995). To define a climate signal, both local and global information need to be preserved, and wavelet analysis is ideally suited for such a purpose (Lau and Wang 1995; Torrence and Compo 1998). A summary of the mathematical formulation of a wavelet transform is given below based on expositions by Lau and Weng (1995) and Torrence and Compo (1998). For most geophysical time series, it is suitable to choose a continuous wavelet transform with complex valued wavelets (Weng and Lau 2004). The wavelet transform of a discrete time series  $x_n$  is defined as the convolution of  $x_n$  with a scaled and transformed mother wavelet  $\psi$ 

$$W_n(s) = \sum_{n'}^{N-1} x_n \boldsymbol{\psi} * \left[ \frac{(n'-n)\delta t}{s} \right]$$
(3.1)

where the \* indicates the complex conjugate, s is the scale, and  $\delta t$  and N are the time spacing and length of the time series  $x_n$ , respectively. The scale s is a dilation parameter that controls the window width and oscillation period of the mother wavelet.

The Morlet wavelet is a commonly used daughter (or an analyzing) wavelet for signal detection in geophysical data (Chapa et al. 1998). It has a better spectral resolution than, for example, the Mexican hat wavelet (Baliunas et al. 1997) and is given by

$$\psi_0(\eta) = \pi^{-1/4} e^{i\omega_0 \eta} e^{-\eta^2/2}$$
(3.2)

where the nondimensional frequency  $\boldsymbol{\omega}_0$  is taken as to be 6, and  $\eta$  is a nondimensional time parameter. The calculations of the wavelet transform (Eq. 3.1) are performed in Fourier space

$$W_n(s) = \sum_{k=0}^{N-1} \hat{x}_n \hat{\psi} \ast (s \omega_k) e^{i \omega_k n \delta t}, \qquad (3.3)$$

where  $\hat{\psi}(sw)$  is a Fourier transform of  $\psi(t/s)$ ,  $\boldsymbol{\omega}_k$  is the angular frequency defined by

$$\boldsymbol{\omega}_{k} = \begin{cases} \frac{2\pi k}{N\delta t} & : k \leq \frac{N}{2} \\ -\frac{2\pi k}{N\delta t} & : k > \frac{N}{2} \end{cases}$$
(3.4)

and  $\hat{x}_n$  is the discrete Fourier transform of  $x_n$ 

$$\hat{x}_k = \frac{1}{N} \sum_{n=0}^{N-1} x_n e^{-2\pi i k n / N}.$$
(3.5)

To ensure that the wavelet transforms at each scale *s* are directly comparable to each other and to the transforms of other time series, the wavelet function at each scale is normalized to have unit energy (Torrence and Compo 1998) and is given as

$$\hat{\psi}(s\omega_k) = \left(\frac{2\pi s}{\delta t}\right)^{1/2} \hat{\psi}_0(s\omega_k)$$
(3.6)

where  $\hat{\psi}_0(s\omega_k)$  is the Fourier transform of the Morlet wavelet.

The wavelet spectrum  $W_n(s)$  in Eq. 3.3 is a matrix of energy coefficients of the decomposed time series at each scale and time, and the coefficient magnitudes show how well the wavelet matches with the time series (Mwale and Gan 2005). The wavelet power spectrum, defined as  $|W_n(s)|^2$  is a good measure of the magnitude of the analyzed time series at each scale. The wavelet transform (Eq. 3.3) is essentially a bandpass filter of uniform shape and varying location and width and can be used to reconstruct the original time series or to obtain a wavelet-filtered time series between any two scales  $j_1$ ,  $j_2$  (Torrence and Compo 1998). For such arbitrary scales  $j_1$ ,  $j_2$ , the filtered time series  $x'_n$  is given by

$$x'_{n} = \frac{\delta j \delta t^{1/2}}{C_{\delta} \psi_{0}(0)} \sum_{j=j1}^{j=j2} \frac{\Re \{W_{n}(s_{j})\}}{s_{j}^{1/2}},$$
(3.7)

where the factor  $\psi_0(0)$  removes the energy scaling,  $C_{\delta}$  is a constant,  $\Re$  denotes the real part of the wavelet spectrum, and  $\delta_j$  is a factor for scale averaging.

Finally, for nonorthogonal wavelet analysis, an arbitrary set of scales can be used to build up a more complete picture of the spectra. For convenience, the scales are taken as fractional powers of two such that

$$s_j = s_0 2^{j\delta j}, j = 0, 1, 2, ..., J$$
 (3.8)

$$J = \delta j^{-1} \log_2(N \delta t / s_0), \tag{3.9}$$

where  $s_0$  is the smallest resolvable scale and usually is taken as  $2\delta t$ , J determines the largest scale, and  $\delta j$  depends on the width in spectral-space of the wavelet function. For this study, the wavelet analysis software developed by Torrence and Compo (1998) will be used to decompose and filter rainfall into its major modes of variability. The software was downloaded from <u>http://paos/colorado.edu/research/wavelets</u>.

# 3.3 Large-scale circulation

### 3.3.1 Summary of regional climatology

A brief overview of regional climatology is provided to facilitate the discussions and focus on the relevant circulation patterns and synoptic systems. Fig. 3.1 presents long-term average climatological patterns for May-October 1970-99. At the surface, much of the Horn of Africa is dominated by a meridional ridge that forms a wedge of weak high pressure over the highlands of Ethiopia. This semi-permanent ridge extends from the Mascarene high through the Mozambique Channel and forms a weak high over southern Ethiopia (Fig. 3.1a). The St. Helena high over the southern Atlantic Ocean features a weak meridional ridge across the Gulf of Guinea (Fig. 3.1a). This high-pressure cell is the source of the southeast trades that blow over the tropical Atlantic and enter western Africa from the southwest. The moist monsoon winds converge towards drier northeast trade winds originating from the Azores high. The ridge associated with the Azores high runs across the Mediterranean Sea into northeast Africa (Fig. 3.1a). The equatorial trough of low pressure running through Africa, the Arabian Peninsula, and the Indian subcontinent generally lies north of 10°N across the Horn of Africa (Fig. 3.1a). The northward penetration of the semipermanent ridge that runs through the Mozambique Channel towards Ethiopia appears to limit the monsoon trough to the north of/over northernmost parts of Ethiopia.



FIGURE 3.1a. Long-term May-October average climatological pattern of mean sea level pressure (hPa) for 1970-99.



FIGURE 3.1b. Same as Fig. 3.1a except for resultant wind speed (contours, m s<sup>-1</sup>) and wind vectors (arrows, wind scale shown at the right corner, m s<sup>-1</sup>) for 850 hPa. Contour interval is 5 m s<sup>-1</sup>.

Cross-equatorial southwesterlies west of Ethiopia reach about 15°N and extend vertically from 1000 hPa (not shown) up to 850-hPa (Fig. 3.1b). The shallow westerlies across central Africa reaching Ethiopia may sometimes originate from central Africa or the Indian Ocean (Folland et al. 1991). However, inspection of daily maps shows westerlies originating from the tropical Atlantic that cross equatorial Africa to reach the Horn. Other notable circulation features at 850 hPa are the diffluent southerlies over southern Ethiopia, the southwesterly low-level jet (LLJ) off the Somali coast, the dry northerlies over northeast Africa north of 15°N, and the weak cyclonic center over Yemen extending into eastern portions of Ethiopia.



FIGURE 3.1c. Same as Fig. 3.1b except for 700 hPa.

With the strengthening of the Saharan and Arabian anticyclones at 700 hPa, dry northerlies prevail across much of the Horn of Africa (Fig. 3.1c). A weak trough running westward from India reaches coastal parts of eastern Africa and marks the disappearance of the LLJ at this level. In the mid to upper troposphere (Fig. 3.1d), easterly winds strengthen with height and develop into an easterly jet that maximizes at 150 hPa over the Horn of Africa (e.g., Segele and Lamb 2005). The core of the jet lies to the south of India and its axis passes across Ethiopia. The TEJ is fed by the anticyclonic circulation around the Tibetan high to the north and the anticyclone over the Indian Ocean to the south (Chen and van Loon 1987). The ridges associated with these highs are evident in Fig. 3.1d along 22°N and 12°S, respectively.



FIGURE 3.1d. Same as Fig. 3.1b except for 150 hPa.
The three dimensional structure of the regional circulation is revealed by the local-Hadley-like and Walker-like circulations shown in Fig. 3.2. The regional Hadley-like (Walker-like) circulation was obtained by averaging the vertical and meridional (zonal) winds over  $30-50^{\circ}$ E (5-20°N). Since the pressure velocity numerical values are much smaller than the horizontal winds, the wind vectors are obtained after dividing the actual values of the horizontal and vertical winds by their respective standard deviation for the entire domain. Hence, the normalized horizontal winds are given in m s<sup>-1</sup> (standard deviation)<sup>-1</sup> and pressure velocities are in Pa s<sup>-1</sup> (standard deviation)<sup>-1</sup>.

The long-term longitude-height cross section (Fig. 3.2a) shows strong ascending motion below 500 hPa for the Horn of Africa. The low- to midtropospheric ascending motion is overlain by descending motion between 400-200 hPa east of 40°E, reflecting the desert-like climate in the northern Rift Valley. Much of western Ethiopia (west of 40°E), on the other hand, show less strong but deep convection extending to 200 hPa. In both cases, centers of maximum convection largely are above the surface between 850-700 hPa. The structure of this mean vertical motion over the Horn of Africa is different from the structure of the mean ascending motion over India (IN) and (especially) over the Bay of Bengal (BB), both of which have deeper and stronger convection reaching to 200 hPa, with centers of maximum convection below 850 hPa over India and at about 300 hPa in the Bay of Bengal.



FIGURE 3.2. Long-term May-October climatology of regional circulation components for 1970-99. (**a**) Longitude-height section of zonal wind (u) and negative vertical velocity (- $\omega$ ), averaged over 5-20°N. (**b**) Latitude-height section of meridional wind (v) and negative vertical velocity (- $\omega$ ), averaged over 30-50°E. Shading depicts actual pressure vertical velocity (- $\omega$ ; Pa s<sup>-1</sup>). See text for explanation of the wind vectors. Vertical dashed dark lines mark the bounding longitudes and latitudes of the Horn of Africa. Red triangle shows the location of Addis Ababa (central Ethiopia). Letter marks in (a) show regional locations (see text).

Inspection of Fig. 3.2a also reveals noticeable differences in the vertical motion fields between the Horn of Africa and West Africa (Guinea-Bissau/Guinea-Conakry, GN), with the mean vertical ascending motion for the latter being deeper. In addition, the maximum ascending motion over West Africa occurs at lower levels below 850 hPa. The trans-North African vertical structure of the ascending motions is consistent with model simulation results of Cook (1997), who found differences between West and East Africa monsoons and

noted that, unlike the situation over West Africa, mid-tropospheric condensational heating is the primary force for low-level convergence and vertical motion over Ethiopia (Section 2.3). The difference in the level of maximum ascending motion between the two regions also is a reflection of the fact that much of the Ethiopian surface (excluding the Rift Valley, southern, and the extreme western Ethiopia) is above 850 hPa.

The long-term average meridional overturning (Fig. 3.2b) is characterized by ascending southerlies at low levels extending to southern Ethiopia, strong ascending motions in the equatorial trough region between 15-20°N, and returning northerly currents at upper levels south of 5°N. The fact that the strongest ascending motion lies north of 15°N is consistent with the ITCZ being located north of Ethiopia during the monsoon season. This is in agreement with the previous assessment of the equatorial trough position near the Horn of Africa sector (Fig. 3.1a). The main rain belt lags a few degrees south of the ITCZ, coinciding with areas of weaker but deeper ascending motions west of 40-42°E (west of the upper-level subsiding current in Fig. 3.2a) and south of 10-12°S. Much of the middle to upper troposphere south of 5°N is characterized by sinking motion and coincides with the climatologically dry southern regions of Ethiopia. The next section provides quantitative assessment of how this climatology relates to the average march of daily rainfall for May-October over the Horn of Africa.

## 3.3.2 Diagnostic Analysis of Regional Circulation Associated with May-October Rainfall

Correlation analyses are used to identify large-scale circulation patterns that are strongly related to rainfall over the Horn of Africa. First, the average daily and 5-day (pentad) rainfall for 1970-99 was computed using 100 Ethiopian stations, which have their main rainy season during boreal summer (Segele and Lamb 2005; present Fig 3.3). This averaging (obtained by adding all available station rainfall, including zero, and dividing it by the number of stations for each day) produced a time series of 184 (days per year) x 30 (years) daily and 36 (pentad per year) x 30 (years) pentad rainfall values. In addition, pentad CMAP rainfall estimates were averaged for 30-50°E and 5-20°N (Fig. 3.3) for 1979-99 because the CMAP data set is available beginning 1979 on a pentad basis.



FIGURE 3.3. Domains used in the study. (**a**) Shaded region shows the Ethiopian monsoon region for which raingauge data from 100 stations are averaged. The rectangle encompasses the Greater Horn of Africa for which pentad CMAP average is computed. The large domain covers the region of atmospheric circulation analysis. (**b**) Domain for teleconnection investigation.

The linkage between the daily (based on Ethiopian raingauge)/pentad (based on raingauge for Ethiopia and CMAP rainfall estimates for the Greater Horn) rainfall averages and grid fields of dynamic and thermodynamic atmospheric variables covering 30°W-90°E and 40°S-50°N (Fig. 3.3a) was examined using correlation and regression analyses. To investigate the relative importance of teleconnection and regional circulation features on daily and 5-day time-scales, correlations between regional rainfall and sea level pressure and horizontal winds over the tropical Pacific Ocean also were performed. Fig. 3.3 shows the different regions used for the data averaging and analyses. Note that as indicated in Section 2.5, some of the Ethiopian stations located close to Djibouti (raingauge stations in northeastern Rift Valley and eastern Ethiopia), Eritrea (stations in northern Rift Valley and northern and northwestern Ethiopia), northern Somalia (stations in the extreme eastern Ethiopia), and eastern Sudan (stations in the extreme southwestern, western and northwestern Ethiopia) possess the climate of the neighboring country/region. In some cases, the distance between borderline stations in Ethiopia and stations in bordering countries is less than the average distance between nearby stations within Ethiopia. Therefore, noting the proximity and orographical similarity between borderline stations in Ethiopia and the neighboring regions, the all-Ethiopian rainfall (raingauge) can be considered to represent the climate of the Horn of Africa. However, the specific data used in subsequent analysis (daily and pentad raingauge data for Ethiopia or pentad CMAP rainfall estimates for the Horn of Africa) will be stated explicitly.

Pearson correlation coefficients were computed to examine the relationship between daily average rainfall and several daily average time series of atmospheric variables for May-October 1970-99 (5520 daily data points). Likewise, the correlations between 5-day average Ethiopian rainfall/CMAP and several atmospheric variables were calculated for the same period as above. In this case, each pair has 1080 pentad data points. Lagged correlations also were performed to assess the stability of the correlation analysis and to test the short range predictability potential for the region. When computing lagged correlation between rainfall and MSLP, the MSLP is shifted backward in time so that rainfall leads MSLP by the number of "lag" days. For example, for a lag correlation of 10 days, the MSLP time series valid for, say July 10, is correlated with the rainfall time series valid for July 20. The total data points used for lagged correlations are 5520 minus "lag" for the daily time series, or 1080 minus "lag" for the pentad time series. Because of the large number of degrees of freedom for these data pairs, we note that even small correlation values would have high statistical significance.

The Mascarene and St. Helena highs generally are considered to be linked to rainfall over the Horn of Africa (e.g., Korecha and Barnston 2006). The

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correlation between daily MSLP and Ethiopian daily average summer rainfall shows that the stronger positive correlations (0.42-0.45) are with the meridional ridge along the Mozambique Channel and the weak meridional ridge over the Gulf of Guinea (Fig. 3.4a), and not with the Mascarene high proper. These strong correlations manifestations of the positive effects of the are southerly/southwesterly flow across much of the continent reaching the Horn of Africa (Fig. 3.1b). In addition, the importance of the Atlantic Ocean, possibly as a moisture source, is evident by the large coverage of statistically significant (0.01%) level) correlations there.

The strongest negative correlations (-0.60) between Ethiopian rainfall and MSLP come from the monsoon trough regions over the Arabian Peninsula, especially over the Yemen highlands extending to Oman. This strong negative correlation reflects the stronger dynamical effects of the monsoon trough; the deeper the monsoon trough, the stronger the low-level convergence. This promotes development of strong convective systems over the Yemen highlands, which propagate westward and produce wetter conditions over Ethiopia. In addition, a deepening of the monsoon trough increases cross equatorial flow, which also favors wetter conditions in Ethiopia.

Figure 3.4b shows a 20-day lagged correlation between rainfall and MSLP. Correlations generally are strong and follow the same pattern as the concurrent



FIGURE 3.4. Spatial patterns of concurrent (**a**) (**c**) and 20-day lagged (**b**) correlations between May-October Ethiopian daily rainfall (raingauge) and mean sea level pressure (MSLP) for 1970-99. Thick solid (dashed) lines enclose positive (negative) correlation values significant at the 99.9% confidence level according to a two-tailed Student's t-test. Ethiopia is delineated in top two panels.

correlations. The strong negative correlations over the Arabian Peninsula (especially over Oman) and positive correlations over south-central Africa reflect the positive roles of the monsoon low pressure systems and the meridional pressure gradient formed by the deepening of the monsoon trough to the northeast and the intensification of the high pressure cells to the south. Clearly, regional MSLP anomalies possess strong predictive potential on short (less than 6 days) and medium (a week to less than a month) time-scales. The same correlation analyses based on pentad CMAP rainfall show similar correlation patterns, but the magnitudes are weaker (not shown).

To examine the possible effects of more remote forces on Ethiopian summer rainfall, Fig. 3.4c shows the correlation between tropical Pacific and eastern Indian Ocean MSLP and daily average summer rainfall for Ethiopia. The primary features of this correlation map are the absence of any connection between rainfall and pressure over the equatorial Pacific and, particularly, the manifestation of weak all-positive correlations over the southern tropical Pacific Ocean. This weak correlation of same polarity over the southern Pacific signifies the absence of connection between the Southern Oscillation Index (SOI) and summer rainfall, and thus implies that regional circulation anomalies (monsoon trough, pressure systems over Indian and Atlantic oceans) are more important than teleconnection effects of ENSO on shorter time-scales. There is, however, significant association between Ethiopian rainfall and MSLP over northern Australia (Fig. 3.4c).

Lower tropospheric geopotential height also shows strong associations with Ethiopian rainfall, with positive correlations south of 10°N and negative correlations in the monsoon regions from the Arabian Peninsula to India at low levels (Fig. 3.5a). This pattern extends to 850 hPa and possesses nearly identical



FIGURE 3.5. Spatial patterns of concurrent correlations between May-October Ethiopian daily rainfall (raingauge) and geopotential height (top) and temperature (bottom) for 1970-99. (**a**) 850 hPa, (**b**) 150 hPa, (**c**) 1000 hPa, and (**d**) 200 hPa. Thick solid (dashed) lines enclose positive (negative) correlation values significant at the 99.9% confidence level according to a two-tailed Student's t-test.

pattern as in Fig. 3.4a. Over the tropical Atlantic Ocean, positive lower tropospheric geopotential anomalies enhance monsoon westerlies across western

and central Africa, which tend to increase rainfall over the Horn of Africa. The positive correlations over the Arabian Peninsula to the north and negative correlations over the eastern parts of Africa and the Mozambique Channel to the south indicate increased Ethiopian rainfall is associated with steep meridional height gradients resulting from the deepening of the monsoon trough and the intensification of the southern hemisphere subtropical highs. At and above 700 hPa, the correlations weaken with height in both hemispheres, but strong positive correlations again appear over much of the northern hemisphere at upper tropospheric levels north of 10°N (Fig. 3.5b). The associated intensification of upper tropospheric subtropical ridge in the northern hemisphere is manifest in the strengthening of the TEJ. Except for areas of statistically significant negative correlations at and near the equator, there is no significant association between rainfall and southern hemisphere upper tropospheric geopotential heights (Fig. 3.5b). Generally, rising (falling) heights in the southern hemisphere at lower (upper) levels favor increased rainfall activity over the Horn of Africa (Figs. 3.5a, b). On the other hand, rising (falling) heights in the northern hemisphere at lower (upper) levels reduce rainfall in the region. Thus, the correlation patterns indicate that the combined effects of cross-equatorial flow at low-levels and dynamics at upper levels determine rainfall anomalies in the Horn of Africa. As with MSLP, the correlations between rainfall and geopotential heights are insignificant over the tropical Pacific Ocean (not shown).

The correlation between regional rainfall and tropospheric temperatures in Figs. 3.5c, d show strong (statistically significant at 99.9% level) and horizontally and vertically coherent correlations that are consistent with the results obtained for geopotential heights. Positive correlations cover much of the northern hemisphere north of about 15°N while negative correlations dominate to the south, with the exception of positive correlations over the Congo rainforest that extend from the surface (Fig. 3.5c) up to 850 hPa (not shown). The northern hemisphere positive correlations between rainfall and temperature persist up to 200 hPa (Fig.3.5d), but unlike for geopotential heights, weaken appreciably at 150 hPa (not shown). The negative correlations between rainfall and temperature in the southern hemisphere generally weaken with height and reverse sign over the climatological location of the Mascarene high (Fig. 3.5d).

It is interesting to note the anomalous positive correlations surrounding the Congo rainforest region in Fig. 3.5c. Although weaker, noticeable correlation contrasts also appear on the correlation maps for MSLP and lower tropospheric geopotential heights (especially at 1000 hPa) surrounding the Congo rainforest (not shown). This anomalous condition is likely related to the contrasting thermal and radiative flux properties of a transpiring extended vegetation cover and a relatively dry barren surrounding land (e.g., Anthes 1984). Examination of the regional temperature/height/MSLP patterns shows that temperatures are warmer in the Congo rainforest region compared to the surrounding area (not

shown). The warm pool extends from the surface up to 850 hPa. Although geopotential heights/MSLP over the Congo rainforest tend to be lower than geopotential heights/MSLP in the surrounding region from the surface (especially) up to 850 hPa, the geopotential height/MSLP differences between the rainforest and the surrounding region are not as strong as the difference in the temperature field (not shown). This is reflected in the correlation patterns around the Congo rainforest in Figs. 3.4a, 3.5a, c.

The dynamical connection between the Horn of Africa rainfall and the regional circulation patterns can be seen from the correlation analyses between rainfall and horizontal winds (Fig. 3.6). Lower tropospheric zonal winds extending from the surface up to 850 hPa over the tropical monsoon regions across all of North Africa and South Asia are strongly positively correlated with Ethiopian rainfall (Fig. 3.6a). The strongest correlations cover much of the eastern portions of the Horn of Africa, most of the Red Sea and the Gulf of Aden, and the northern Arabian Sea and the adjoining coastal areas. Thus, stronger westerlies across the entire monsoon region indicate enhanced moisture inflow and a robust monsoon for the Horn of Africa. The region of maximum correlations over the Gulf of Aden/Red Sea and the adjoining areas corresponds to the locations of a climatological low-level wind confluence (Fig. 3.1b) and covers the regions where initial convective storm development occurs (often,

thunderstorms develop over the highlands of Yemen and over the eastern lowlands of the Horn of Africa in the afternoon; e.g., Segele and Lamb 2005).



FIGURE 3.6. Spatial patterns of concurrent correlations between May-October Ethiopian daily rainfall (raingauge) and zonal wind (top) and meridional wind (bottom) for 1970-99 at 850 hPa (**a**) (**c**), and 150 hPa (**b**) (**d**). Thick solid (dashed) lines enclose positive (negative) correlation values significant at the 99.9% confidence level according to a two-tailed Student's t-test.

Consistent with the equatorward tilt of the ITCZ with height and increasing depth of the monsoon flow, the maximum positive correlation over the monsoon region shifts southward between 700-500 hPa (not shown). Farther south (2.5°S, 67.5°E), there is a strong negative low-level correlation over the equatorial Indian Ocean buffer zone of anticyclonic signature that forms as the southeasterlies recurve after crossing the equator (Fig. 3.6a). This strong negative correlation, i.e., strong easterlies leading to wet conditions over Ethiopia, indicates that moisture inflow into the Horn of Africa from the Indian Ocean increases when the southeasterlies south of the equator are stronger and the westerlies just to the north are weaker (less deflection of winds). This area of negative correlation is limited to the lower troposphere (1000-850 hPa). In the subtropical regions north of about 15°N and extending from West Africa to India, negative correlations appear at and above 700 hPa and further strengthen with height and become the dominant pattern in the tropical upper troposphere (Fig. 3.6b).

The correlation between middle to upper tropospheric zonal winds and Ethiopian rainfall becomes very strong at 150 hPa (Fig. 3.6b) where the TEJ also locally maximizes over Ethiopia (Segele and Lamb 2005). Strong negative correlations with magnitudes exceeding 0.5 cover a broad latitudinal band across the monsoon regions, with a maximum negative correlation (-0.54) over northern Ethiopia and at a few locations in western and northern Africa. At 200 hPa, the maximum negative correlation primarily spans central Ethiopia (8°-12°N; not shown). The precise process by which the TEJ affects rainfall is not known at this stage. Overall, the positive association between the TEJ and Ethiopian rainfall is linked to upper level divergence that favors stronger vertical motions, organized convective systems, and subsequently enhanced rainfall over the Horn of Africa (e.g., Kanamitsu and Krishnamurti 1978; Chen and van Loon 1987, Hastenrath 2000a).

The correlation between rainfall and meridional wind reveals the critical monsoon components that affect rainfall over the Horn of Africa both at low and upper levels (Figs. 3.6c, d). In the lower atmosphere extending from the surface up to 850 hPa, an area of strong positive correlation covers the northern Arabian Sea that coincides with the location of the northern branch of the LLJ, while strong negative correlations appear over the monsoon trough regions across the Gulf of Aden, Red Sea, Yemen high grounds, and northeastern Ethiopia (Fig. 3.6c). The fact that the maximum positive correlation coincides with the climatological position of the northern branch of the LLJ indicates that a strong LLJ surge off the Somali coast is an important ingredient of a strong monsoon over the Horn of Africa. These centers of positive and negative correlations tilt westwards with height (1000-600 hPa) while weakening (not shown). The negative correlations over the monsoon trough regions and positive correlations to the south over the Arabian Sea imply stronger low-level convergence in the monsoon trough associated with stronger northerlies along the Red Sea and the

surrounding regions and strong southerlies over the Arabian Sea, and hence stronger monsoon trough and enhanced rainfall over Ethiopia (Fig. 3.6c).

The dominant feature in the upper levels is the strong negative correlations over southern India and equatorial Indian Ocean that attain peak values at 150 hPa and weak positive correlations over northwestern Ethiopia (Fig. 3.6d). These correlation patterns indicate that the northerlies (southerlies) that flank the TEJ over southern India (northwest Ethiopia) enhance rainfall over the Horn of Africa, possibly by increasing upper level divergence associated with the ensuing diffluent flow as the easterlies over southern India (northwest Ethiopia) turn southward (northward).

As was the case for pressure and height fields, no statistically significant association was found between horizontal winds over the Pacific Ocean and rainfall over the Horn of Africa (not shown). It is to be noted that the time series for the correlation analyses are constructed of daily data containing short-term fluctuations. As a result, the overall correlation reflects not only the interannual variability but also the intraseasonal and shorter time-scale fluctuations. The latter variability would not be present if the time series were constructed of monthly rainfall, in which case the time averaging would have purged all shortterm fluctuations, and thus the correlation analyses would have shown primarily the large-scale interannual variability linked to the ESNO phenomenon. Because of the absence of statistically meaningful correlations in the equatorial Pacific, it is reasonable to infer that at shorter time-scales only regional circulations determine the variability of the monsoon in the region.

To identify and quantify the structure of the anomalous regional Walkertype circulation and the local meridional circulation, the horizontal winds and vertical velocity were regressed onto the average Ethiopian daily rainfall for standard pressure levels between 1000-100 hPa (i.e., 1000, 925, 850, 700, 600, 500, 400, 300, 250, 200, 150, and 100 hPa). This method was used by Krishnamurthy and Goswami (2000) to establish the linkage between the Indian monsoon and the ENSO phenomenon on interdecadal time-scales. In particular, the authors investigated the monsoon meridional circulation and the equatorial Walker circulation by regressing zonal winds and vertical velocities onto a low-pass filtered All-Indian monsoon rainfall. Following this approach, we linearly regressed the above atmospheric fields onto daily average Ethiopian rainfall. The least squares regression of Y on X is expressed as

$$Y = aX + b (3.10)$$

where a is the slope and b is the intercept of the linear fit. The equation can be simplified if the variables are expressed as departures from the time averages; i.e., x=X-mean(X); y=Y-mean(Y), in which case, the regression equation is simplified to

$$y = coefficient^* x \,. \tag{3.11}$$

In the subsequent regression analysis, Eq. 3.11 is employed using daily anomalies of u, v,  $-\omega$ , and rainfall. These anomalies were calculated at each of the 2.5° by 2.5° latitude-longitude grid points (Figs. 3.3a, b) and 12 tropospheric levels for u, v, and  $-\omega$  by subtracting the time mean of the respective May-October 1970-99 time series from the corresponding daily values (184 days per year x 30 years daily data points). Hence, each daily three dimensional grid anomaly is a departure from the long-term climatology of the corresponding grid. The daily anomalies for average Ethiopian rainfall (184 days per year x 30 years daily data points)/Horn of Africa CMAP pentad rainfall estimates (36 pentads per year x 30 years pentad data points) were computed in the same way. The regression coefficients, signifying a response in the dependent variables (u, v, and  $-\omega$  anomalies) due to a change in the independent variable (rainfall anomalies), are then averaged over 5-20°N to obtain the mean Walker-type circulation and over 30-50°E to get the mean local meridional circulation anomalies at 12 tropospheric levels. Figure 3.7 shows the regional circulations corresponding to positive anomalies of daily average rainfall (raingauge) for Ethiopia.

During active phases of the monsoon over the Horn of Africa, the regional mean Walker-type circulation generally is enhanced throughout much of the monsoon latitudinal belt between 5-20°N (Fig. 3.7a). It can be inferred from the strong anomalous vertical motions in Fig. 3.7a corresponding to positive



FIGURE 3.7a. Regional circulations associated with positive anomalies of average Ethiopian daily rainfall (raingauge) showing a longitude-height section of regression of zonal wind (u) and negative vertical velocity (- $\omega$ ) on regional rainfall averaged over 5-20°N. Wind vector anomalies are constructed in the same way as Fig. 3.2; horizontal wind anomalies are in m s<sup>-1</sup> (standard deviation)<sup>-1</sup>, and vertical velocity anomalies are given in Pa s<sup>-1</sup> (standard deviation)<sup>-1</sup>. Shading depicts actual regression coefficients for vertical velocity anomalies (- $\omega$ ; Pa s<sup>-1</sup>). Vertical dashed dark lines mark the bounding longitudes for Ethiopia. White triangle shows the longitude and elevation of Addis Ababa (central Ethiopia). Letter symbols at top show regional locations (see text).

Ethiopian rainfall anomalies that there is strong connection between the monsoon phases over Ethiopia and over Guinea-Bissau/Guinea-Conakry (GN), eastern Chad/western Sudan (CS), India (IN), and the Bay of Bengal (BB). The

strongest anomalous ascending motion over the Horn of Africa occurs in the middle to upper troposphere and favors wetter conditions especially over western Ethiopia. In addition, this anomalous ascent acts to weaken the descending motions that appear from mid- to upper-levels in the mean regional circulation east of 40°E (Fig. 3.2a), and therefore enhances wetter conditions in the climatologically dry areas of the eastern and northeastern Ethiopia.

However, strong anomalous descending motions develop at lower levels between 40°-55°E (Fig. 3.7a) where climatologically weak descending motions (Fig. 3.2a) exist, thereby acting to intensify the subsiding current there. Clearly, the performance of the monsoon over the dry regions of the Horn of Africa is determined by the interaction of the lower and upper level local ascending motions. In general, the regional anomalous Walker-type circulation associated with the positive phase of the Horn of Africa monsoon (i.e., above average rainfall) is characterized by stronger low-level westerlies (upper level easterlies) below 700 hPa (above 300 hPa), stronger low-level descending motion east of 40°E, and stronger ascending motion over the major monsoon regions.

Note that the area average daily rainfall is likely to be biased towards the wetter regions (western/southwestern Ethiopia) that receive higher intensity rainfall. As a result, area average rainfall totals reflect the dominant variability but may not represent regional variations correctly. However, our aim here is to

understand the overall performance of the monsoon (irrespective of the variations within the region) for which this use of non-standardized rainfall is recommended (e.g., Folland et al. 1991). Standardized data will be used in due course when the relative variations of rainfall over the Horn of Africa are important.

The local anomalous meridional circulation corresponding to a stronger monsoon over Ethiopia is enhanced by the strengthening of the southerlies from surface up to 700 hPa and the returning northerlies above 300 hPa (Fig. 3.7b). The strongest ascending anomalies are co-located with the climatological center of maximum ascent between 850-700 hPa north of 15°N (Fig. 3.2b), which indicates the occurrence of a more active monsoon over the Horn of Africa in association with a stronger ITCZ north of Ethiopia. This anomalous ascent extends farther north (~ 22°N) and weakens the climatological northern hemisphere descending motion (Fig. 3.2b) there. Concurrently, a broad anomalous descending motion prevails south of about 5°N and intensifies the mean meridional circulation in the southern hemisphere (Fig. 3.2b). Part of this anomalous descending motion extends farther to the north at low levels and intensifies the climatologically weak descent north of 10°N (Figs. 3.2b, 3.7b).

Similar zonal and meridional circulations are observed when pentad CMAP rainfall (averaged over 30-50°E and 5-20°N) is used (Fig. 3.8). The primary

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FIGURE 3.7b. Same as Fig. 3.7a except for latitude-height section of regression of meridional wind (v) and negative vertical velocity (- $\omega$ ), on rainfall averaged over 30-50°E. Vertical dashed dark lines mark the bounding latitudes for Ethiopia. White triangle shows the latitude and elevation of Addis Ababa (central Ethiopia).

differences in this case are the stronger lower to middle tropospheric anomalous ascent over eastern Chad/western Sudan(CS) and the stronger mid- to upper tropospheric ascent and lower tropospheric descent over the Horn of Africa corresponding to positive CMAP pentad rainfall anomalies over the Horn (Fig. 3.8a). The structure of the local meridional circulation is close to the one obtained using Ethiopian raingauge data, except that the circulation magnitudes are stronger (Fig. 3.8b).



FIGURE 3.8a. Same as Fig. 3.7a except for Pentad CMAP rainfall estimates for the Horn of Africa (5-20°N, 30-50°E).



FIGURE 3.8b. Same as Fig. 3.7b except for Pentad CMAP rainfall estimates for the Horn of Africa (5-20°N, 30-50°E). Vertical dashed dark lines mark the bounding latitudes for the Horn of Africa.

## 3.3.3 Summary of Diagnostic Analysis

The correlation and regression analyses discussed in the above section provided a three-dimensional picture of the regional circulation patterns directly linked to rainfall variability over the Horn of Africa. In general, the strength of the monsoon in the region is characterized by a stronger meridional pressure gradient east of about 30°E associated with the intensification of the Mascarene high over the southern Indian Ocean and deepening of the monsoon trough across the Arabian Peninsula. This northward-directed gradient extends up to 850 hPa but weakens appreciably above 700 hPa. The primary domain of influence of the subtropical highs is limited to the west of about 70°E, and is manifest by a meridional ridge that runs along the eastern coastal regions of Africa and by the intensification of pressure over the Gulf of Guinea. In particular, it is interesting to note that the Mascarene high east of 70°E exerts little influence on the Horn of Africa weather. On the other hand, the intensification the Atlantic basin enhances of pressure over westerly/southwesterly flow across much of western and central parts of the continent and creates wetter conditions over the Horn of Africa. Other important factors associated with the Horn of Africa rainfall are the LLJ off the coast of Somalia and the northerlies over the Red Sea and the surrounding regions. Generally, strong and deep southerlies over the northwestern Arabian Sea and strong northerlies over and to the north of the monsoon trough are associated with a strong monsoon over the Horn of Africa.

The impacts of southern hemisphere atmospheric conditions generally weaken above 700 hPa, but the northern hemisphere systems above 700 hPa exert a stronger influence on the Horn of Africa rainfall. Generally, higher geopotential heights and warmer temperatures north of about 20°N and above 500 hPa enhance wet conditions over the Horn of Africa. The maximum forcing comes from regions of largest gradients in geopotential heights just north of the subtropical ridge at 150 hPa, at which level the equatorward meridional temperature gradient associated with the Tibetan high collapses, with temperatures at that level gradually increasing polewards into midlatitude regions in both hemispheres. Associated with the collapse of this temperature gradient, no statistically significant association between Ethiopian rainfall and tropospheric temperature is found at and above 150 hPa. One of the most important tropical forcings at upper levels comes from the TEJ, with the strongest association occurring at 150 hPa. Generally, a stronger TEJ over a broad latitudinal belt of the monsoon region with strong northerlies over southern India enhances rainfall over the Horn of Africa. This work has further associated TEJ and monsoon rainfall variability over Ethiopia.

The analysis has provided a substantial number of specific parameters and their locations that could be used as predictors in statistical models. The strong degree of coherent variability of the monsoon over the Horn of Africa and the various regional atmospheric parameters suggests a high predictability potential for the region at short and medium range time-scales. However, because atmospheric processes are nonlinear, the overall rainfall variability is determined by nonlinear interactions of the different atmospheric processes that occur at different time and spatial scales (Barnston et al. 1994; Webster and Hoyos 2004). Thus, although each of the above identified processes/synoptic conditions linearly correlate with rainfall, their utility in predicting low frequency events might be impacted by the atmosphere's chaotic tendencies (Barnston et al. 1994). One approach to this problem is to isolate the different modes of variability in the time series and treat each mode separately, thereby eliminating the impacts of the nonlinear interactions (Webster and Hoyos 2004). This approach will be employed next in the current study. First, a diagnostic study will be made to identify regional circulation features associated with the dominant modes of rainfall variability in the region. This diagnostic study is crucial for developing improved medium and longer (a month to seasons) range forecasting tools for the region. The discussion in this section provides the essential background for the time-scale separation approach used in the next section.

## 3.3.4 Dominant Modes of May-October Rainfall Variability

Most naturally occurring phenomena in the earth's weather and climate system exhibit variability on multiple time-scales (Weng and Lau 1994). The Horn of Africa monsoon rainfall is one such climatic element that possesses variability ranging from intraseasonal to interannual to decadal and longer timescales (e.g., Gissila et al. 2004; Segele and Lamb 2005; Korecha and Barnston 2006). A number of studies have documented the interannual variability of rainfall, but studies of the intraseasonal variability for Ethiopia have begun only recently (e.g., Segele and Lamb 2005) and, to date, none have comprehensively identified all modes of such variability. As indicated earlier, isolating the different modes of rainfall variability is essential to understand the interactions among the different time-scales and assess the predictability of monsoonal rainfall for the region. This is the main motivation for this section.

Over the past several decades, the Horn of Africa experienced few flood years, but many drought years. The irregularity in flood and drought events and the magnitude of variability with time constitutes nonstationarity (e.g., Mwale and Gan 2005). Nonstationarity hampers the use of Fourier transform, the most commonly used tool for power-frequency spectrum analysis, which assumes homogeneity and stationarity in the time series (e.g., Weng and Lau 1994; Baliunas 1997; Torrence and Compo 1998). The Fourier transform maps a signal from time to frequency domain and provides the distribution of total variance in the data as a function of frequency, but does not reveal possible changes of the oscillation characteristics with time (e.g., Wang and Wang 1996). An appropriate and relatively new tool to analyze time series that contain nonstationarity/weak power at many different frequencies is the wavelet transform (Weng and Lau 1994; Torrence and Compo 1998). Unlike the Fourier transform, the wavelet transform localizes a signal in both frequency and time domains. It uses generalized base functions (wavelets) that can be stretched and translated with a flexible resolution (e.g., Weng and Lau 1994; Torrence and Compo 1998). Thus, using wavelet analysis, we will be able to isolate and examine the temporal characteristics of the dominant modes of rainfall variability over the Horn of Africa. We will employ one of the most commonly utilized wavelet functions, the complex Morlet wavelet, which is known to have a better spectral resolution than, for example, the Mexican hat wavelet (Baliunas 1997).

Local and global wavelet spectra were computed for daily, 5-day, and monthly raingauge data for Ethiopia, and pentad CMAP rainfall estimates for the Horn of Africa between 5-20°N and 30-50°E. Figure 3.9 shows a result of such wavelet analysis of average daily Ethiopian rainfall for 1970-99. The daily average all-Ethiopian rainfall time series (Fig. 3.9a) is aligned (vertically) with a time-frequency plot of the power associated with daily rainfall variability (Fig. 3.9b). The time frequency plot (Fig. 3.9b) shows the distribution of the rainfall variance in time (abscissa) for all Fourier periods (ordinate). The statistical significance of the local power is assessed by comparison with a red noise background spectrum. Following Torrence and Compo (1998), the red noise is estimated from a lag autocorrelation coefficient of 0.75 determined from the relation  $\left(\alpha_1 + \sqrt{\alpha_2}\right)_2'$ , where  $\alpha_1$  and  $\alpha_2$  are lag-1 and lag-2 autocorrelations of the rainfall time series. The thick dashed line in Fig. 3.9b delineates the Cone of



FIGURE 3.9. (a) Time series of mean daily all-Ethiopian May-October rainfall (raingauge) for 1970-99. (b) Local wavelet spectra of time series in (a) (mm<sup>2</sup>), where the thick dashed line is the Cone of Influence (COI) (described in the text). (c) Global wavelet spectra (local power averaged over the period 1970-99) expressed as percentage of total variance; the annual cycle explains about 20% of the total variance. (a) and (b) use the same abscissa for easy identification of the power at any given time. (b) and (c) share the same ordinate for easy comparison of the local and global power. The black solid contour in (b) encloses areas of greater than 95% confidence for a red noise process with a lag correlation coefficient of 0.75, determined from  $(\alpha_1 + \sqrt{\alpha_2})/2$ , where  $\alpha_1$  and  $\alpha_2$  are lag-1 and lag-2 autocorrelations of the rainfall time series (Torrence and Compo 1998).

Influence (COI), the region of the wavelet spectrum (below the COI line) in which edge effects become important. Because of the finite length of the data, errors will occur at the beginning and end of the wavelet power spectrum. One solution is to "pad" the end of the time series with zeroes before doing the wavelet transform and remove them afterwards. Padding with zeroes, however, introduces discontinuities, and as one goes to larger scales, the amplitude near the edge decreases as more zeroes enter the analysis (e.g., Torrence and Compo 1998; Mwale and Gan 2005). The global wavelet spectrum (Fig. 3.9c) is the time average of the local power in (b) for each Fourier period and uses the same ordinate as (Fig. 3.9b). Unlike the local wavelet spectrum, which is expressed in absolute value (mm<sup>2</sup>), the global power at a given frequency is expressed as a percentage of the total global power summed over all frequencies.

The variance associated with the annual cycle is the dominant power in the wavelet spectra (Fig. 3.9b, c) accounting for about 20% of the total average global variance. It is clear from the local wavelet spectra (Fig. 3.9b) that the variability of rainfall at the annual scale shows very little fluctuation as there are few variations in the magnitudes of the power in most years. The power associated with rainfall variability at shorter time-scales (less than 10 days) is small, but it shows more fluctuations in the 1990s (Fig. 3.9c). There are relatively strong variances at a period of 45 days in the late 1970s. Isolated but significant energy can also be observed at seasonal, biennial, and ENSO time-scales. For time-scales

between 90-180 days, isolated but strong energies in the late 1970s and mid 1980s (Fig. 3.9b) cause a noticeable peak in the global power (Fig. 3.9c). The most significant power is that occurring in 1987, where there is large variability in the daily rainfall. That year was one of the driest years for Ethiopia since the early 1960s.

At the biennial time-scale (with a period of about 2-yr or 730 days), large energies are evident in both the local spectrum (Fig. 3.9b, note the strong power in mid 1970s, 1980s, and 1990s), and the global power spectra (Fig. 3.9c). Also, there are significant energy spikes in both the local and global power spectra at a period of about 4 years (1460 days). This is linked to large variances during the late 1970s and 1990s (Fig. 3.9b) associated with ENSO in the 3-7-yr band (1090-2550 days). On the other hand, during the 1980s, spikes of energy cluster on the seasonal to biennial time-scales and are conspicuously absent on the 3-7-yr band.

To examine how the power spectrum for the CMAP data compares with the observed Ethiopian raingauge data, wavelet analysis was performed on pentad CMAP rainfall estimates, which are generally of smaller magnitude (Fig. 3.10). The layout/construction of Fig. 3.10 is identical to Fig. 3.9 as just discussed. Although the time spans for the two data sets are different, there are noticeable differences as well as a degree of similarity in the temporal structure of the local (Figs. 3.9b, 3.10b) and global (Figs. 3.9c, 3.10c) power spectra for the two time



FIGURE 3.10. Same as FIG. 3.9 except for pentad CMAP rainfall estimates for the period 1979-99. Regional average of pentad CMAP rainfall estimate was computed over 30-50°E and 5-20°N.

series. One of the main differences between the two data sets is the absence of a broadly distributed variance on the annual time-scale (Fig. 3.10b) compared to Fig. 3.9b. As a result, for the CMAP time series, the power associated with the annual cycle accounts for substantially smaller portions of the total global variance for the entire frequencies. Thus, for the CMAP data, the percentage of the global variance at the 1-yr period compared to the total global variance for the entire period is only 7.7%, while for the daily Ethiopian rainfall, this percentage is about 20% (Figs. 3.9c, 3.10c). This power is primarily associated

with spikes of energies in the mid to late 1980s and mid 1990s (Fig. 3.10b). Another significant difference is in the strength of rainfall variability associated with the biennial and ENSO modes. For the daily Ethiopian data, the variances associated with the biennial and ENSO modes are weak in the 1980s (Fig. 3.9b), but the local spectra for the CMAP data features strong energies in these two modes (Fig. 3.10b). The large variance in 1987 centered at the 730-day period in Fig. 3.10b is noteworthy. The difference in the power spectra between the raingauge and CMAP data sets probably is due to the fact that (1) the CMAP data generally underestimate rainfall and (2) the Horn of Africa domain (30°-50°E, 5°-20°N) over which the CMAP data are averaged includes desert areas north of Eritrea. Hence, the 5-day rainfall average and the interannual rainfall variability for the entire domain may be significantly reduced.

One of the similarities in the power spectra for the CMAP and Ethiopian raingauge data is the frequency distribution pattern of the global wavelet spectra (Figs. 3.9c, 3.10c); both show peaks at the seasonal, annual, biannual, and ENSO time-scales. The temporal structures of the local wavelet spectra for the two time series also reveal similarity at the intraseasonal and seasonal time-scales (Figs. 3.9b, 3.10b), both of which show isolated spikes of high energy in 1987 at the 45-180 days band. An interesting feature to note is the relatively large variability of the rainfall rates in 1987 (Fig. 3.10a). This large variability is associated primarily

with heightened activities at intraseasonal (20-90-day) and seasonal (160-200day) time-scales as evidenced by the high power at these bands in Fig. 3.10b.

The differences between the CMAP and raingauge data still exist when compared with the wavelet spectra for 5-day average all-Ethiopian rainfall (Fig. 3.11). This may not be surprising when we note the substantial differences between the two time series (e.g., Figs. 3.10a, 3.11a). There are, however, similarities in both the local and global power spectra for the two time series. Excluding the differences in the magnitude of the variance, especially at the annual time-scale, both time series exhibit relatively large variances at the intraseasonal, seasonal, biennial, and ENSO time-scales (Figs. 3.10b, 3.11b). The similarity is more visible on the global wavelet spectra (Figs. 3.10c, 3.11c). Notwithstanding the magnitude differences, the two power spectra bear strong resemblance in the frequency distribution of the global power.

The wavelet analyses for daily and 5-day average all-Ethiopia rainfall reveal strong pattern similarity between the two local spectra (Fig. 3.9b, 3.11b). The major difference is in the magnitudes of the power and its frequency structure, which occurred due primarily to the temporal averaging. Note especially that the disappearance of short time (less than 15-20 days) fluctuations in the power of the 5-day averaged time series as expected (Fig. 3.11b). As a result, the annual cycle for the 5-day spectra accounts for ~ 15% of the total global variance, which



FIGURE 3.11. (a) (b) Same as Fig. 3.9a, b except for 5-day average all-Ethiopian rainfall (raingauge). (c) Global wavelet spectra of 5-day average all-Ethiopian May-October rainfall for 1970-99. The amplitude is normalized by total variance over the entire time-scales. Insets magnify the major peaks at indicated time-scales.
is less than the case for the daily data (Figs. 3.9c, 3.11c). Other than these small differences, the two time series show a very high degree of similarity in the global power spectra (Figs. 3.9c, 3.11c). Because one of the goals of this study is to develop prediction models at intraseasonal and seasonal time-scales, and since the 5-day averaging helps in smoothing out very high frequency variability while retaining the details at the intraseasonal, interannual, and longer time-scales, we chose to use 5-day average all-Ethiopian rainfall (raingauge) for subsequent analyses. Despite the better spatial coverage provided by the CMAP data, we chose to use the Ethiopian raingauge data because the CMAP data significantly underestimate the amount of rainfall and its variability (cf. Figs. 3.10a, c 3.11a, c). In addition, the CMAP data are available beginning from only 1979, and hence the number of years that could be used for interannual variability study would be substantial reduced. Thus in the subsequent sections of this Chapter, the Ethiopian raingauge data will be used.

The peaks in the 5-day rainfall (raingauge) global wavelet spectrum are used to identify temporal domains of coherent modes of variability. The primary modes of variability are highlighted and magnified in Fig. 3.11c (insets). At intraseasonal to seasonal time-scales, three peaks can be identified with wavelet bands of 10-50, 50-135, and 135-220 days. On the annual time-scale, there is a prominent band spanning 0.6-1.5 years. There are two peaks on the biennial-ENSO time-scale in the bands 1.5-2.1 and 2.1-3.1 years, which are not sufficiently separated. Finally, on longer time-scale a prominent energy is localized in 3.1-6.8yr band. This is termed the ENSO/Low-frequency mode. Although there are other small peaks at longer time-scales, their variances likely are affected by the aforementioned zero padding and will not be considered here.

The above association of the 1.5-3.1 and 3.1-6.8 yr bands as biennial-ENSO and ENSO/Low-frequency modes, respectively, is consistent with the fact that the fundamental modes of variability in global sea level pressure (SLP) and sea surface temperatures (SST) fields at the 1.5-3-yr and 3-7-yr bands are represented as the biennial and ENSO modes, respectively (e.g., Barnett 1991; Shen and Lau 1995; Webster et al. 1998; Chang and Li 2000). However, there are differences in the frequency ranges associated with these modes. For example, Torrence and Webster (1999) identified the 2-8-yr band in wavelet spectra of SST and SOI as the ENSO mode. In addition, the dominant modes differ from location to location. Shen and Lau (1995) noted that the dominant mode for the southeast Asian monsoon regions, eastern Indian Ocean, and western, northern, and southern Pacific Ocean occurs on a biennial time-scale, while much of central and eastern Pacific and northern Indian oceans show spectral peaks on 3-6-yr band. Recently, Lau and Wu (2001) found that the strong monsoon-ENSO connection tends to occur with a pronounced 2-yr polarity switch in basin-scale SST anomalies, and recommended that the monsoon-ENSO relationship be considered in pairs of years.

For our case, the 1.5-3.1-yr band is taken as the biennial-ENSO mode. The first reason is the absence of clear separation in the spectral peaks at the 1.5-2.1yr and 2.1-3.1 bands. Second, as will be noted later, the 2.1-3.1-yr band most likely represents the ENSO effects on Ethiopian May-October rainfall better than the 3.1-6.8-yr band. Although the spectral separations slightly differ when 5-day average all-Ethiopian June-September rainfall (raingauge) was used, the amplitude of the anomalies associated with the longer time-scale ENSO mode is small. The variability with periods of 3.1-6.8 years is hereafter referred to as the ENSO/low frequency variability.

After the frequency bands of coherent variability are identified, the next step is to filter the corresponding time series using Eq. 3.7 but on finer resolutions for accurate reconstruction/filtering. For the 5-day average May-October rainfall time series, N=1080,  $\delta t = 1/36$  yr,  $s_0 = \delta t$ ,  $\delta j = 0.1$ , and J=500. For these sets of values, the reconstruction of the time series from the wavelet transform has a mean square error of 0.041 mm. The same sets of values are used to construct the filtered time series shown in Fig. 3.12. More than 97% of the total variance is explained by the first four filtered series (10 days to 1.5 years).

To identify regional circulation patterns that are directly related to the above modes of rainfall variability, all atmospheric variables discussed in Sections 3.3.1

and 3.3.2 were identically bandpass filtered using the wavelet bands identified for rainfall. The results are discussed in the next section.



selected wave bands shown in Fig. 3.11.

### 3.3.5 Regional Circulations Associated with the Dominant Modes of

# May-October Rainfall Variability

Wavelet analysis was performed on MSLP, and on horizontal and vertical winds, vertical velocity, geopotential height, temperature, relative humidity (RH), and specific humidity at all standard pressure levels from 1000-100 hPa (1000-300hPa for RH and specific humidity) over the region covering 30°W-90°E

and 40°S-50°N depicted in Fig. 3.3. In addition, derived quantities such as horizontal wind divergence, vertically integrated moisture, and moisture and temperature advection were analyzed. The wavelet banding of the atmospheric variables uses the frequency bands obtained for the 5-day all-Ethiopian rainfall (raingauge) time series (Section 3.3.4). Correlation and regression analyses were then performed on the filtered 5-day average rainfall and identically filtered pentad time series of gridded atmospheric variables (1080 data points) to identify atmospheric conditions and regional circulation features that are associated with rainfall variability at each time-scale. To avoid repetitiveness, only regional features with the highest correlations will be discussed.

# 3.3.5.1 Variability on Intraseasonal Time-Scale (10-50 days)

There are few statistically significant associations between 10-50 day banded Ethiopian rainfall and the regional atmospheric variables in the domain. The primary elements that show significant correlations with rainfall are local moisture (RH and specific humidity) and low-level horizontal winds. Figure 3.13 shows the spatial patterns of concurrent correlations between identically 10-50 day banded rainfall and specific humidity at 1000 hPa and vertically integrated moisture from the surface to 300 hPa. Enhanced rainfall in the 10-50 day band occurs in association with increased moisture in the lower to middle troposphere in the region. Similar correlation patterns were also found for RH (not shown).



FIGURE 3.13. Spatial patterns of concurrent correlations between reanalysis fields and Ethiopian rainfall (raingauge) that are identically wave banded for the 10-50 day period. (a) Specific humidity at 1000 hPa. (b) Vertically integrated water vapor  $\frac{1}{g} \int_{300}^{P_s} q dp$ , where q is specific humidity (kg kg<sup>-1</sup>), g is the acceleration due to gravity (m s<sup>-2</sup>), and the integral is from surface (P<sub>s</sub>) to 300 hPa. Thick solid red line encloses correlation values significant at the 99.9% confidence level according to a two-tailed Student's t-test.

The importance of deep moisture at the intraseasonal time-scale is reflected by the strong positive correlation between rainfall and vertically integrated moisture (maximum correlation of +0.5) shown in Fig 3.13b. Next to atmospheric moisture, local circulations exert noticeable influence on rainfall. This is reflected in a weak positive but statistically significant correlation (maximum correlation magnitude of +0.3) between 10-50 day wave banded Ethiopian rainfall and lowlevel horizontal wind components over the Horn of Africa (not shown). Derived local and regional atmospheric quantities (e.g., horizontal wind convergence and advection of moisture and temperature) were examined for possible links with the 10-50 day wave banded rainfall, and moderate correlations of about +0.3 (significant at 99.9% level) with moisture advection and horizontal wind convergence at 700 hPa were found.

In addition, a possible link between MJO and 10-50 day wave banded rainfall was examined. The MJO was identified by applying a wavenumber-frequency spectral analysis of satellite observed outgoing long-wave radiation (OLR) over the tropical latitude (15°S-15°N) as discussed in Wheeler and Kiladis (1999; the code was graciously provided by Dr. George Kiladis, NOAA/OAR Earth System Research Laboratory, Boulder, Colorado). However, no connection (r  $\sim$  0) was found between the MJO and rainfall over the Horn of Africa at intraseasonal time-scale. This finding of the absence of MJO link with Ethiopian rainfall demonstrates the clear difference between the Horn of Africa and South Asian monsoons for which MJO plays a dominant role at the intraseasonal time-scale (e.g., Madden and Julian 1971; Webster et al. 1998; Krishnamurthy and Shukla 2000; Annamalai and Slingo 2001; Lawrence and Webster 2002). Thus, moisture (e.g., Fig. 3.13) and local dynamics (low-level horizontal winds and convergence) appear to be the primary factors that affect rainfall over the Horn of Africa at intraseasonal time-scale.

#### 3.3.5.2 Variability on Sub-Seasonal Time-Scale (50-135 days)

The larger-scale regional atmospheric conditions reflected in the reanalysis data become more relevant and exert stronger influence on rainfall variability at longer time-scales. However, local features, especially moisture and low levelconvergence and upper level divergence, still play an important role in affecting rainfall. Figure 3.14 shows correlation maps for selected parameters that exhibit the largest connection. Locally, rainfall variability at the 50-135 day periodicity is related to low-level convergence (Fig. 3.14a) and upper level divergence (not shown). A strong regional effect is identified over the Arabian Sea, where strong northerly components in the TEJ enhance rainfall over the Horn of Africa (Fig. 3.14b). Vertically integrated water vapor, especially over Ethiopia, Djibouti, northern Somalia, and Yemen highlands profoundly influences Ethiopian rainfall at 50-135 day period (Fig. 3.14c).

Lower tropospheric moisture (surface to 925 hPa; not shown) over the tropical Atlantic Ocean south of the equator exhibits weak to moderate positive association with Ethiopian rainfall (r ~+0.3), indicating that the tropical Atlantic Ocean serves as a moisture source for the Horn of Africa. This is consistent with our earlier findings of strong positive climatological correlations between rainfall and lower tropospheric westerly flow across western and central Africa. Additional evidence of the effects of tropical Atlantic Ocean is the positive correlation between rainfall and lower tropospheric temperatures in the Atlantic



FIGURE 3.14. Spatial patterns of concurrent correlations between reanalysis fields and Ethiopian rainfall (raingauge) that are identically wave band filtered for the 50-135 day period. (a) Horizontal wind convergence at 700 hPa; (b) meridional wind at 200 hPa; (c) same as Fig. 3.13b except for the 50-135-day band; and (d) temperature at 1000 hPa.. Thick solid (dashed) lines enclose positive (negative) correlation values significant at the 99.9% confidence level according to a two-tailed Student's t-test.

Ocean, with the strongest correlation at 1000 hPa (Fig. 3.14d). Increased nearsurface temperature closely reflects SST and implies increased evaporation as well as large water holding capacity of the air, both of which increase the lowlevel tropospheric water content. Advected by the low-level westerly flow, the moist and warm air could enhance rainfall over the Horn of Africa. However, this correlation is the opposite of the overall correlation pattern in Fig.3.5c, which shows strong negative correlation between rainfall and temperature over the Gulf of Guinea at the same level. To examine the thermodynamic and dynamic tropospheric features leading to enhanced/deficient rainfall over Ethiopia, composite maps were constructed by stratifying the filtered large-scale flow patterns according to the magnitudes of the filtered rainfall anomalies shown in Fig. 3.12 (top row, second column).

To construct composite maps, 9 cases of negative anomalies less than -2.5 mm d<sup>-1</sup> and 11 cases of positive anomalies greater than 2.5 mm d<sup>-1</sup> were selected from the filtered rainfall time series. All these extreme cases occurred in the beginning and towards the end of the season (i.e., in May and October), during which time midlatitude frontal systems affect the weather in the Horn of Africa. Horizontal winds and temperatures were extracted from the 50-135 day filtered reanalysis fields for the same calendar dates of the above identified cases and averaged appropriately. Fig. 3.15 depicts the anomalous flows and temperatures associated with positive/negative Ethiopian rainfall departures at this time-scale.



FIGURE 3.15. Large-scale anomalous flow (vectors; m s<sup>-1</sup>) and temperature anomalies (shading; K) associated with the negative (left; **a**, **c**) and positive (right; **b**, **d**) phases of Ethiopian rainfall (raingauge) anomalies at sub-seasonal time-scale (50-135 days). Top panel is for 850 hPa (**a**, **b**) and the bottom panel is for 150 hPa (level of easterly jet maximum; **c**, **d**). Rainfall anomaly thresholds are  $\pm$  2.5 mm d<sup>-1</sup> and correspond to about the top/bottom 1% of the filtered rainfall time series in Fig. 3.12 (upper right panel).

During the negative phase (i.e., dry conditions over Ethiopia), anomalous dry northeasterly trades prevailed over much of the Horn of Africa (Fig. 3.15a). This indicates weak monsoon conditions for the Horn of Africa. At upper levels, anomalous easterlies/southeasterlies over the tropical Indian Ocean appear to have strengthened the TEJ (Fig. 3.15c). However, with the anomalous low-level northerlies and hence drier atmosphere, the upper level dynamics by itself were not sufficient to produce wet conditions. On the other hand, the positive phase (i.e., wet conditions over Ethiopia), exhibited weakened low-level monsoon flow, with anomalous easterlies (westerlies) at low (upper) levels over the Arabian Sea/northern Indian Ocean (Fig. 3.15b,d). The low-level anomalous easterlies were associated with anomalous anticyclone over the Arabian Sea, a feature that serves as the main moisture source for the spring rains (short rains) in Ethiopia during February/March-May. The upper level westerly anomalies result from southward intrusions of Mediterranean frontal system, consistent with the strong cold temperature anomalies to the northeast of Ethiopia. These features are frequently observed during the short season.

The Atlantic Ocean provided additional support for increased wet conditions during the positive phase. From the surface up to 850 hPa, anomalous warm moisture laden westerlies streamed from the Atlantic Ocean into the Horn of Africa (Fig. 3.15b). In addition to advecting moisture, the westerlies appeared to have increased the low-level convergence over Ethiopia. Thus, positive temperature anomalies over the Atlantic Ocean tend to increase moisture incursions and enhance rainfall over the Horn of Africa at sub-seasonal timescale. However, much of the large-scale circulation features that favored the wet conditions are "non-monsoon" origin.

It is clear from Fig. 3.15b that the westerlies are associated with the anomalous cyclonic flow over southern Atlantic while the positive temperature anomalies appear to be linked to the northern hemisphere center of maximum positive temperature anomaly. In contrast, the climatological westerlies in Figs. 3.1b are associated with the St. Helena high and the weak meridional ridge across the equatorial Atlantic. Likewise, the correlation patterns of Fig. 3.5c link temperatures hydrostatically to local pressure. Hence, the origins of wind and temperature anomalies are different for the raw time series containing all temporal components and the wave band filtered sub-seasonal time series of 50-135 day periodicity.

## 3.3.5.3 Variability on Seasonal Time-Scale (135-220 days)

The circulations associated with the seasonal cycle exhibit stronger connections between Ethiopian rainfall and large-scale atmospheric systems. However, most of the correlations found are opposite to the correlation patterns previously obtained for all time-scales combined, as discussed in Section 3.3.2. This opposite relationship is illustrated in Fig. 3.16, which shows correlations



FIGURE 3.16. Spatial patterns of concurrent correlations between Ethiopian rainfall (raingauge) and regional reanalysis fields for time series identically banded at 135-220 days period: (a) Mean sea level pressure (shading) and horizontal winds at 1000 hPa (vector); (b) temperature (shading) and horizontal winds (vector) at 700 hPa; (c) same as (b) except for 500 hPa; and (d) zonal wind (shading) and horizontal winds (vector) at 150 hPa. Thick solid red (dashed) lines enclose positive (negative) correlation values significant at the 99.9% confidence level according to a two-tailed Student's t-test for the shaded fields. Correlations between rainfall and horizontal winds are shown as vectors, with unit vector (bottom right inset in each panel) representing a correlation magnitude of 1.0.

between wave band filtered Ethiopian rainfall and regional pressure, temperature, and horizontal winds for different levels. Negative anomalies of mean sea level pressure are generally associated with enhanced Ethiopian rainfall on seasonal time-scale (Fig. 3.16a). The location of the strongest negative correlation over the eastern Mediterranean Sea suggests extratropical forcing associated with the southward intrusion of Mediterranean frontal lows. Corresponding to the surface pressure patterns, westerly/southwesterly wind anomalies at 1000 hPa over western Africa and anomalous northeasterlies (northwesterlies) north (south) of the equator over the Indian Ocean (i.e., antimonsoon anomalous flow) act to increase Ethiopian rainfall. Throughout the lower- to mid-troposphere, temperature anomalies over the Atlantic and Indian oceans exhibit positive correlations with Ethiopian rainfall at the seasonal timescale (Fig. 3.16b, c).

At the level of the TEJ (Fig. 3.16d), the strong positive correlations across much of India and Arabian Peninsula indicate that upper level westerlies/northwesterlies enhance rainfall over Ethiopia. This, again, is in stark contrast to the climatological correlation map of Fig. 3.6b. In general, the lack of hemispheric contrasts in the correlation patterns for MSLP and temperature, the absence of statistically significant correlations over much of the monsoon regions east and north of Ethiopia in the MSLP chart, the existence of anti-monsoon anomalous correlations at low-levels, and the prevalence of westerlies at upper levels indicate that the seasonal mode of variability is primarily composed of non-monsoon signatures and greatly affected by extra-tropical systems.

Composite analysis of the 135-220 day band filtered time series indicated that during the positive phase corresponding to positive rainfall anomalies over Ethiopia, surface pressure tends to be low over much of the domain except over India and the Arabian Sea (not shown). On the other hand, during the negative phase, positive surface pressure anomalies prevail. These pressure anomalies are primarily associated with the strength and southward penetration of northern hemisphere midlatitude systems. The filtered time series for wind also shows the prevalence of upper level westerlies (not shown) over much of the monsoon region. Further examination of the data revealed that nearly all the extreme positive/negative anomalies occurred primarily during May and October, rather than during the peak of the monsoon season. This confirms that most of the variance in the seasonal cycle is associated with westerly systems that affect the region during May and October. Note that although the monsoon rain starts early in May and ceases late in October over the wetter regions of Ethiopia (e.g., Segele and Lamb 2005), the monsoon flow is fully established only during June-September when the monsoon rain covers most of northern and eastern parts of the Horn of Africa. The effects of including May and October rainfall in the analysis will be investigated later in this chapter.

## 3.3.5.4 Variability on Annual Time-Scale (0.6-1.5 years)

The dominant variability in the Horn of Africa monsoon rainfall primarily is associated with the annual cycle. This variability largely is composed of fluctuations in the major elements of the monsoon systems that modulate monsoonal rainfall over the Horn of Africa. This is reflected in exceptionally strong correlations between the filtered rainfall time series and the different atmospheric fields. The correlation maps exhibit very similar spatial patterns as the overall correlation maps of Section 3.3.2, except that in this case the correlation values are strong in nearly all atmospheric variables considered (r > |0.9|). Figure 3.17 shows the spatial correlation patterns for 0.6-1.5-yr band.

Enhanced rainfall over the Horn of Africa is associated with negative pressure anomalies in the equatorial trough and positive anomalies over southwestern Indian Ocean and large portions of the Atlantic (Fig. 3.17a). The correlations are exceptionally strong (r > |0.93|) in the monsoon trough over the Arabian Peninsula, across the subtropical ridge over the Gulf of Guinea/southern Atlantic basin, and along the meridional ridge that runs through the Mozambique Channel. The region of weakest correlation over Africa parallels the ITCZ located a few degrees to the north.

The position of the ITCZ over Africa and the monsoon trough over the Arabian Peninsula and India are best represented by the convergence/trough in



FIGURE 3.17. Same as Fig. 3.16 except for time series identically wave band filtered at the 0.6-1.5 year band.

the correlation vectors, which parallel the mean flow at the same level, especially over the eastern sector. The correlation magnitude between rainfall and the horizontal winds is very strong (maximum correlation > |0.94|) at low levels (Fig. 3.17a). These vectors display a well-established cross-equatorial flow over the Indian Ocean/Arabian Sea and strong northerlies over the Arabian Peninsula/northeast Africa, indicating a high degree of correlation between Ethiopian rainfall and regional monsoonal winds. The similarity between the correlation vectors and the mean flow over the Atlantic Ocean and over parts of West Africa weakens compared to the strong resemblance between the correlation vectors and the mean flow over the Indian Ocean because only the zonal winds show strong connection with Ethiopian rainfall.

Wave band filtered (0.6-1.5 yr) tropospheric temperatures from 1000-200 hPa also exhibit strong associations with filtered summer rainfall (e.g., Fig. 3.17b, c shading). Strong positive correlations (> +0.9) north of about 20°N dominate the upper troposphere up to 200 hPa, but weaken appreciably at and above 150 hPa (not shown). The hemispheric correlation contrasts in Fig. 3.17b, c are similar to the overall correlation pattern for the unfiltered time series (e.g., Fig. 3.5c, d) except that the present correlations for the time series filtered at the annual frequency bands are exceptionally strong (maximum positive correlation  $\sim$  0.96).

At 700 hPa, the strongest signals in the correlation vectors occur primarily in the Northern Hemisphere associated with the monsoon trough in the east and the Azores anticyclone to the west, with correlation magnitudes exceeding +0.95 (Fig. 3.17b). The intensification of the Azores anticyclone creates strong northerly/northeasterly winds over central Sahara and the Arabian Peninsula that strongly negatively correlate with Ethiopian rainfall, i.e., northerlies enhance rainfall. Southwesterly winds over the Gulf of Guinea and equatorial Africa positively correlate with Ethiopian rainfall, but the climatological wind pattern at 700 hPa is dominated by easterly/northerly winds, which partly originate in northern hemisphere subtropical regions. Hence, the weakening of the Sahara/Arabian anticyclone reduces the monsoon over the Horn of Africa by weakening the northerlies north of the ITCZ/monsoon trough, but simultaneously enhances rainfall by diminishing the easterlies/northerlies in the Atlantic and equatorial Africa.

The correlation vectors at 500 hPa (Fig. 3.17c) depict similar correlation patterns except that the zonal (meridional) components over the subtropical regions are stronger (weaker), signifying the growing influence of easterlies beginning in the mid-troposphere. The zonal wind correlation at this level is strong negative (> |0.9|) north of 10°N (20°N) over Africa (India) and strong positive (> +0.9) to the south. The region of strong negative correlation (>|0.9|) between waveband filtered Ethiopian rainfall and zonal winds expands southward with height and covers a broad latitudinal belt between the Equator and 25°N at 200 hPa (not shown). The strong signature of the easterly jet at upper levels is marked by the prevalence of easterlies in the correlation vectors over much of the tropics (Fig. 3.17d). The magnitude of the highest correlation between wave band filtered (0.6-1.5-yr) Ethiopian rainfall and zonal winds (shading) is about 0.97.

The correlation between wave band filtered (0.6-1.5-yr) Ethiopian rainfall and meridional wind undergoes significant changes from the middle to upper troposphere. The strong negative (positive) correlations between filtered Ethiopian rainfall and northerlies over northern Africa/Libya (southerlies over the northern Indian Ocean and Indian Peninsula) at 500 hPa (Fig. 3.17c) weaken with height and reverse sign, and develop into a region of strong positive (negative) correlation at and above 200 hPa (not shown) to the west (east) of Ethiopia at 150 hPa (Fig. 3.17d). This reversal reflects the increasing effects of the tropospheric upper subtropical anticyclone over the Middle East/Pakistan/India. The region of maximum positive correlations between the filtered Ethiopian rainfall and upper tropospheric northerlies lies to the west/northwest of the Tibetan anticyclone/ridge and extends from northwestern Ethiopia to Libya and southern Europe at 150 hPa, while the region of maximum negative correlations lies to the south/southeast of the upper tropospheric anticyclone over the Indian Ocean/Indian Peninsula (Fig. 3.17d). In general, the annual cycle predominantly reflects the variability associated with the southwest monsoon. Consistent with Section 3.3.2, this annul time-scale analysis also identified/confirmed the strong links between the large-scale features/flow patterns and rainfall over Ethiopia.

The regional meridional and Walker circulations associated with the annual cycle are almost identical in pattern to the climatological circulation features discussed in Section 3.3.1, and will not be presented here. Instead, we focus again on the characteristic flow patterns associated with the extreme cases of positive and negative phases of rainfall over Ethiopia. The stratification was performed by selecting the top and bottom 1 percent of the filtered rainfall time series (rainfall anomaly threshold of  $\pm 3.0$  mm d<sup>-1</sup>). The composite results for selected atmospheric variables at 850 and 200 hPa are shown in Figure 3.18.

The negative phase of the annual cycle is characterized by strong negative temperature anomalies (< -5K) through much of the troposphere over subtropical/midlatitude regions north of 30°N (Fig. 3.18a, c). Concurrently, most of the monsoon region experiences mild warm temperature anomalies (~ 1K) in the lower troposphere. Associated with the extratropical cold air anomalies, large-amplitude temperature trough runs southward into the monsoon system along about 50°E at low levels, and appears to weaken the monsoon trough over the Arabian Peninsula. Note the anomalous northeasterlies (northwesterlies) north (south) of the equator over the Indian Ocean (i.e., anti-monsoon anomalous flow) over the Arabian Sea and western Indian Ocean (Fig. 3.18a). At 200 hPa (Fig. 3.18c), the strong negative temperature anomalies to the east of the Caspian Sea indicate weakened meridional upper tropospheric temperature gradient between the warm elevated Tibetan Plateau to the north and the cooler upper



FIGURE 3.18. Large-scale anomalous flow (vectors; m s<sup>-1</sup>) and temperature anomalies (shading; K) associated with the negative (left) and positive (right) phases of Ethiopian rainfall (raingauge) anomalies for time series wave band filtered for the 0.6-1.5 year cycle. Top panel is for 850 hPa and the bottom panels is for 200 hPa. Rainfall anomaly thresholds are  $\pm$  3.1 mm d<sup>-1</sup> and correspond to about the top/bottom 1% of the filtered rainfall time series.

tropospheric temperatures to the south over the Indian Ocean (especially). The negative temperature anomalies also weaken the warm core Tibetan high, and hence the TEJ, all of which are consistent with the weaker monsoon observed.

On the other hand, during the positive phase (Fig. 3.18b, d), the influence of extratropical frontal systems is weak (temperature anomalies of  $\sim$  -1K), leaving anomalous anticyclonic patterns over the Mediterranean region. Both the northeasterly/northerly trades north of the monsoon trough and the southwesterly monsoon over the Indian Ocean in the south are strengthened (Fig. 3.18b). Additionally, the anomalous low-level westerly flow across western and central Africa further supports an active monsoon over Ethiopia. At upper levels (Fig. 3.18d), strong easterly anomalies enhance the TEJ. Thus, enhanced low-level southwesterly flow over the Indian Ocean, strengthened low-level westerly flow reaching Ethiopia from western Africa, and a strong TEJ are the main characteristics of strong monsoon rainfall over Ethiopia at the annual timescale. It is interesting to note the presence of anticyclonic ridge over northern parts of the Horn of Africa during the active phase (Fig. 3.18b). It is observed by the Ethiopian NMSA that occasionally moist southwesterlies recurve and form anticyclonic inflow over northern Ethiopia, and often result in active monsoon locally. These events are not yet quantitatively studied, but may have high predictive potential and scientific value.

#### **3.3.5.5** Variability on Biennial-ENSO Time-Scale (1.5-3.1 years)

The spectral analysis of 5-day average Ethiopian rainfall (raingauge) shown in Fig.3.11c reveals two variance peaks between 1.5-3.1 years: a smaller peak at 1.84 years, which is associated with the biennial cycle, and a larger one at 2.38 years that is linked to the ENSO variability (Section 3.3.4). However, since there is no clear temporal separation in the power spectrum structure between the two peaks, we consider the power in the 1.5-3.1 years band as joint biennial-ENSOrelated variability.

At this time-scale, variations in the monsoon and subtropical regions of both hemispheres exert a strong influence on Ethiopian rainfall (Fig. 3.19). Shading in Fig. 3.19 shows the spatial patterns of the correlations between rainfall and MSLP/geopotential heights. The vectors in the figure are the regression of horizontal wind anomalies onto rainfall. Following the discussion in Section 3.3.2, the horizontal wind anomalies, wave band filtered at the 1.5-3.1 year band, are linearly regressed onto identically filtered Ethiopian rainfall (raingauge) time-series. The regression coefficients for the zonal and meridional winds regression equations then are the response of the dependent variables (u and v) due to a change in the independent variable (filtered rainfall anomalies). In the northern hemisphere, the strengthening of the Azores/Saharan high produces strong northerlies along the Red Sea that intensify the monsoon trough over the Arabian Peninsula (Fig. 3.19a). Concurrently, the heat low over the Arabian



FIGURE 3.19. Results of regression (vector) and correlation (shading) analyses of time series wave band filtered for the 1.5-3.1 year period. (a) Correlation between MSLP and rainfall (shading) and regression of horizontal winds onto rainfall (vector) at 1000 hPa. (b) Correlation between geopotential height and rainfall (shading) and regression of horizontal winds onto rainfall (vector) at 150 hPa. (c) Same as (a) but the analysis is extended eastward into the tropical Indian and Pacific oceans. (d) Same as (c) except for 200 hPa. Thick solid (dashed) lines enclose positive (negative) correlation values significant at the 99.9% confidence level according to a two-tailed Student's t-test for the shaded fields. The reference vector is in m s<sup>-1</sup> (bottom right corner of each panel).

Peninsula deepens and creates anomalous cyclonic circulation that invigorates the southwesterlies across much of the Horn of Africa. These conditions produce strong wind confluence along the Yemen highlands. The strong correlations associated with the Azores/Saharan high persist through the troposphere (e.g., Fig. 3.19b). At 150 hPa, the highest correlation is linked to the anomalous anticyclone over the Middle East, which acts to strengthen the easterly jet to its south during the positive phase (Fig. 3.19b). The moderate negative correlation over the equatorial Indian Ocean off the coast of Kenya is likely connected to the upper branch of the Walker circulation, with strong easterlies corresponding to wetter conditions over Ethiopia. This feature is, does not contradict the observational analysis results of Hastenrath (2000b) that, climatologically, a closed equatorial zonal circulation during summer is limited to the western Indian Ocean and only in the middle to upper troposphere.

Unlike for the seasonal/annual time-scales, rainfall variations at the biennial-ENSO time-scale show pronounced links to atmospheric variability over the Pacific Ocean (Fig. 3.19c, d). Figure 3.19c shows that the deepening of the monsoon trough over the Arabian Peninsula during high rainfall event over Ethiopia is linked to lower tropospheric negative pressure anomalies in the southern Indian and western Pacific oceans. The strongest signal in the mean sea level pressure field is found in the equatorial western Pacific between 100-140°E (Fig. 3.19c). Farther east, the correlation between rainfall and MSLP reverses sign and intensifies eastward, with positive correlations (>0.84) occurring just east of Tahiti (17.6°S, 149.6°W) in the southern tropical Pacific Ocean. This creates a clear dipolar correlation pattern east and west of about 160°E (Fig. 3.19c).

The low-level horizontal winds regressed upon rainfall (Fig. 3.19c) exhibit strong easterly anomalies over equatorial central and eastern Pacific and westerly anomalies over eastern Indian Ocean, creating a strong region of convergent flow over the Maritime Continent. This flow has been associated with the lower branch of the Walker circulation during the cold ENSO phase (e.g., Lau and Wu 2001). The anomalous southwesterlies off the coast of Somalia are characteristics of strong monsoon.

At upper levels (Fig. 3.19d), the correlation between Ethiopian rainfall and geopotential heights is less strong, but two centers (10°N, 140°W and 15°S, 140°W) of maximum negative correlations coincide with the anomalous anticyclonic circulation in the regression wind vectors. For high Ethiopian rainfall event, much of the amplitude of the regression of the 200 hPa horizontal winds onto rainfall is concentrated along the equator over the central and eastern Pacific (east of 150°E) and over much of the Indian Ocean west of about 80°E. These easterly anomalies indicate a strengthened TEJ. The upper-level cyclonic circulations centered about 10°N,140°W and 15°S,140°W straddling the converging westerlies over the equatorial western-central Pacific, and the upper

level divergence over the Maritime Continent reveal the signature of the anomalous Walker circulation with large-scale ascent over the Maritime Continent and descent over the central-eastern Pacific. These wind patterns are consistent with the regression analysis of Lau and Wu (2001) for the Asian Summer Monsoon and the composite analysis results of Webster et al. (1998) for South Asian and Australian monsoons. In general, positive (negative) pressure and stronger easterly (westerly) wind anomalies over much of the eastern/central Pacific (Indian) ocean at the surface, and enhanced upper level easterly (westerly) anomalies over the Indian Ocean (equatorial Pacific), tend to enhance rainfall over Ethiopia.

The flow structure associated with the extreme positive and negative rainfall phases over Ethiopia further illustrates the regional and teleconnection patterns that affect the rainfall. The stratification of the atmospheric fields is done by selecting rainfall threshold anomalies of ±0.75 mm d<sup>-1</sup> for the extreme positive and negative phases of rainfall. For these thresholds, 11 cases of negative anomalies less than -0.75 mm d<sup>-1</sup> and 15 cases of positive anomalies greater than 0.75 mm d<sup>-1</sup> were identified. Geopotential heights and horizontal winds for 1000 and 200 hPa were extracted for the same dates and averaged appropriately to form composite fields corresponding to the extreme filtered Ethiopian rainfall anomaly cases. Fig. 3.20 depicts difference fields of the composites for geopotential and horizontal winds at 1000 and 200 hPa (corresponding to high



FIGURE 3.20. Distributions of the differences (corresponding to high minus low rainfall phases) between the composites of large-scale flow (vectors; m s<sup>-1</sup>)/height (shading; gpm) anomalies corresponding to about the top/bottom 1% (positive/negative phases) of the rainfall time series filtered at the biennial-ENSO time-scale (1.5-3.1 years). (a) 1000 hPa, (b) 200 hPa, (c) same as (a) but extended eastward across the tropical Indian and Pacific oceans, and (d) same as (b) but extended eastward across the tropical Indian and Pacific oceans. Rainfall anomaly thresholds are  $\pm$  0.75 mm d<sup>-1</sup>.

minus low rainfall phases). There is a striking similarity in the flow patterns between composite difference charts the in Fig. 3.20 and the correlation/regression analysis of Fig. 3.19. At or near the surface, strong Ethiopian monsoon events at the biennial-ENSO time-scale coincide with a deeper monsoon low over the Arabian Peninsula, intensified Azores/Sahara high, and higher geopotential heights over the Mediterranean Sea (Fig. 3.20a). In addition, southwesterlies across Ethiopia and off the coast of Somalia become stronger. Furthermore, the anticyclonic anomalous circulation at the upper levels indicates the intensification of the regional subtropical ridge/high and the strengthening of the TEJ (Fig. 3.20b). The spatial structure of the anomalous anticyclone over eastern Mediterranean Sea (Fig. 3.20b) indicates the presence of southerly components in the TEJ over northwestern Ethiopia and northerly components east of Ethiopia that enhance upper level divergence during wet years. This assessment is consistent with the strong upper tropospheric correlations found between rainfall and meridional winds for the annual mode (Section 3.3.5.4).

The influence of Mediterranean Sea pressure systems on Ethiopian rainfall (i.e., high geopotential height corresponding to enhanced Ethiopian rainfall in Fig. 3.20a) is consistent with previous observational results that indicated strong link between sea level pressure and sea surface temperature over the Mediterranean region and monsoonal rainfall over Africa and India at interannual time-scales (e.g., Ward 1998; Raicich et al. 2003; Rowell 2003). In particular, Raicich et al. (2003) found that Sahel wetness often is associated with higher atmospheric pressure in the western Mediterranean Sea and suggested a local Hadley circulation and its seasonal shifts as basic large-scale physical processes that link the two regions.

The large-scale anomaly structure associated with strong monsoons over the Horn of Africa exhibits large amplitude signatures in horizontal winds over the eastern Indian and the Pacific oceans (Figs. 3.20c, d), further confirming the linkage between the Horn of Africa and ENSO at the biennial-ENSO time-scale. Of particular interest are the anomalous near surface westerlies/northwesterlies over the equatorial Indian Ocean and anomalous easterlies over the equatorial Pacific (Fig. 3.20c). These wind anomaly patterns suggest strong convection over the Maritime Continent that feeds into the ascending branch of the Walker circulation.

At the upper levels, the easterly (westerly) anomalies imply stronger easterly (westerly) jet over the Indian (Pacific) Ocean (Fig. 3.20d). The net effect of strong low-level easterlies and upper-level westerlies over the equatorial Pacific is to enhance the Walker circulation over the equatorial Pacific (Kirtman and Shukla 2000). These anomalous flow patterns (Figs. 3.20c, d) compare well with the circulations associated with strong and weak Indian monsoon composites (e.g.,

Kuwamura 1998, their Figs. 13c, f; Webster et al. 1998, their Fig. 20). There is also strong qualitative agreement between Figs. 3.19c, d and results of model experiments that simulated atmospheric response during ENSO phases (e.g., Lau and Nath 2000, their Fig. 7). In general, the east-west dipolar patterns in the southern tropical Pacific and parts of the Indian Ocean in pressure/height fields, as well as the overall large-scale flow structure associated with the positive (negative) phases of Ethiopian rainfall, are characteristics of a cold (warm) ENSO phase (e.g., Rasmusson and Carpenter 1982, Webster et al. 1998; Garreaud and Battisti 1999; Kirtman and Shukla 2000).

To examine the local effects associated with regional and remote large-scale processes at the biennial-ENSO scale, the local meridional and Walker-like circulations are constructed by regressing the horizontal winds and negative pressure vertical velocity onto 5-day average filtered Ethiopian rainfall time series for standard pressure levels between 1000-100 hPa (Fig. 3.21). Because we are interested in the local (Horn of Africa) response to ENSO, the zonal circulation was obtained by averaging the regression coefficients over 5-20°N (Fig. 3.21a), and not on the equatorial plane. When the zonal vertical circulation was constructed for the equatorial plane (10°S-10°N), the amplitude of the circulation was very weak across the Horn of Africa longitudes. It was decided that the zonal circulation patterns averaged over the Horn of Africa latitudes give a good representation of the local overturning. The local meridional circulation was similarly constructed for the Horn of Africa longitudes between 30-50°E (Fig. 3.21b).





The regional zonal circulation corresponding to a unit positive Ethiopian rainfall anomaly at the biennial-ENSO time-scale shows ascending motions that appear to tilt eastwards with height (Fig. 3.21a). The maximum ascent is located in the lower to middle troposphere, with weaker ascending motion at the upper levels (Fig. 3.21a). This indicates that during high Ethiopian rainfall event, the large-scale flow acts to enhance the mean vertical ascent in the region and weaken the climatological upper level descent east of 40°E (Fig. 3.2). The overall effect thus is to enhance rainfall in the region.

There is strong upper level descent (Fig. 3.21a) just to the west of Ethiopian longitudes and general descent over much of western/central Africa, especially over the longitudes of Guinea-Bissau/Guinea-Conakry (GN) and eastern Chad/western Sudan (CS). This descent may be an indication that the western/central parts of the North African continent and Ethiopia are differently affected at this time-scale. It may also be a result of the location of the latitudinal averaging. For example, the structure of the vertical circulation over West Africa changes substantially when the Walker-type circulation is constructed on the equatorial plane (10°S-10°N). On the other hand, there is coherent variability between the Horn of Africa and South Asia, especially with the monsoon region in the Bay of Bengal (BB) longitudes (Fig. 3.2a).

The meridional circulation also shows strong ascending motion over northern parts of Ethiopia (3.21b). The ascending motion exhibits strong southward tilt with height, bringing much of the Horn of Africa under middle to upper tropospheric ascending motion regime. The primary descending motion is located near the equator in the mid-to-upper troposphere. Thus, during the high Ethiopian rainfall phase at the biennial-ENSO time-scale, the large-scale meridional flow intensifies the ascending motion over the Horn of Africa and the



FIGURE 3.21b. Same as Fig. 3.21a except for latitude-height section of regression of meridional wind (v) and negative vertical velocity (- $\omega$ ), on regional rainfall averaged over 30-50°E. Vertical dashed dark lines mark the bounding latitudes for Ethiopia. White triangle shows the latitude and elevation of Addis Ababa (central Ethiopia).
descending motion near the equator (Fig. 3.21b). The regional circulation for the low Ethiopian rainfall phase is opposite to the circulation in Fig. 3.21 and is obtained by multiplying the regression vectors by -1.0. Thus, during the low Ethiopian rainfall phase, the shift in the Walker-type circulation eastward in the Pacific forces the ascending motion in the regional meridional circulation to shift to the equatorial regions. This shift brings descending motions over much of the Horn of Africa, thereby weakening the climatological ascending motions and consequently rainfall in the region.

To this point, because there is no distinct frequency separation between the biennial and ENSO modes for the 5-day May-October rainfall time series, we have combined the variability associated with the biennial- and ENSO-related modes to identify the large-scale systems involved in modulating Ethiopian rainfall. Before concluding this section, it is necessary to address some related questions. Are the two cycles actually distinct? Could the biennial cycle be a part of the ENSO cycle? How would each modulate the large-scale systems and regional rainfall independently? To address the above issues, it suffices to evaluate the effects of the two modes on rainfall separately. Since the biennial and ENSO modes have clear signals at lower levels (e.g., Fig. 3.19c), the correlations between rainfall and MSLP are computed for the two modes.

Figure 3.22 depicts the correlation between rainfall and MSLP for the biennial and ENSO modes separately. Both modes exhibit strong correlations over the Pacific and eastern Indian Ocean, although the magnitudes are weaker for the biennial time-scale (Fig. 3.22 top). The large dipole in the correlation pattern for the 2.1-3.1-yr band between the Indo-western Pacific region and the southeast Pacific (Fig. 3.22 bottom) is the classical southern oscillation signal (e.g., Barnett 1991).



FIGURE 3.22. Spatial patterns of simultaneous correlations between rainfall and mean sea level pressure for the 1.5-2.1-yr (top) and 2.1-3.1-yr bands (bottom) over the Pacific and eastern Indian oceans. Thick solid (dashed) lines enclose positive (negative) significant values at the 99.9% confidence level according to a two-tailed Student's t-test for the shaded fields.

Inspection of the filtered data for each time-scale revealed that the two modes show a high degree of similarity over subtropical/monsoon regions where the largest regional anomalies occur. Thus, although the dominant variance in the 1.5-3.1-year time-scale is associated with the ENSO cycle, both the biennial and ENSO modes act in harmony to enhance or suppress rainfall over the Horn of Africa. This finding is consistent with Barnett (1991), who noted that the space-time evolution of the SLP/SST field at the biennial band looks much like the traditional ENSO event.

The analysis in this section has identified the regional and remote circulation features that affect the Horn of Africa rainfall variability at the biennial-ENSO time-scale. The primary regional circulation systems that strongly impact regional rainfall at this scale are the Azores high and the associated ridge system along the Mediterranean Sea, the heat low over the Arabian Peninsula, the low level southerlies over Ethiopia and off the coast of Somalia, the low level northerlies along the Red Sea, and the subtropical upper-tropospheric wind patterns over eastern Mediterranean and northeast Africa along 30-35°N that affect the TEJ.

The high degree of association between Ethiopian rainfall and the large-scale circulation features over the Pacific and Indian Ocean is a reflection of the effects of ENSO. The ENSO cycle modulates the regional monsoon through the

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interaction of the Walker-type and regional meridional circulations. In addition, surface pressure variations in the southern Indian Ocean associated with ENSO appear to affect the southerly flow into the Horn of Africa. It is interesting to note that although atmospheric variability in the Atlantic basin/Gulf of Guinea are highly associated with the sub-seasonal and annual modes, no significant association is found at the biennial-ENSO time-scale.

#### 3.3.5.6 ENSO/Low-Frequency Variability (3.1-6.8 years)

The wavelet spectrum for Ethiopian summer rainfall shows a significant variance peak across the 3.1-6.8-year band, with the maximum variance occurring at about 5 years. Since the wavelet power spectra for Niño-3 SST and SOI show broadly distributed power with peaks in the 2-8 year ENSO band (e.g., Torrence and Compo 1998; Torrence and Webster 1999), one could expect a strong degree of association between Ethiopian rainfall and ENSO at the 3.1-6.8-year band. This section examines the variability of Ethiopian rainfall at this time-scale.

The regional surface circulation systems that show stronger correlations with Ethiopian rainfall at this low frequency time-scale are the Mediterranean frontal systems, the ridge associated with the subtropical high, surface pressure over the Congo rainforest, the Mascarene high (especially south of Madagascar), and marginally the St. Helena high (Fig. 3.23a, b). Except for surface pressure over the



FIGURE 3.23. Maps of regression and correlation analyses of time series filtered for the 3.1-6.8-yr cycle. (**a**) Correlation between MSLP and rainfall (shading) and regression of horizontal winds onto rainfall (vector) at 1000 hPa. (**b**) Correlation between geopotential height and rainfall (shading) and regression of horizontal winds onto rainfall (vectors) at 200 hPa. (**c**) Same as (a) but the analysis is extended eastward into the tropical Indian and Pacific oceans. Thick solid (dashed) lines enclose positive (negative) correlation values significant at the 99.9% confidence level according to a two-tailed Student's t-test for the shaded fields. The reference vector is in m s<sup>-1</sup> (bottom right corner of each panel).

Congo rainforest area, which shows a limited vertical extent, the effects of the above listed regional systems extend to at least 500 hPa (not shown). In general,

the deepening of pressure systems over western Mediterranean Sea and the intensification of the Mascarene high tend to increase rainfall over Ethiopia.

Comparisons of the regional circulation systems associated with the biennial-ENSO and the ENSO/low frequency modes (Figs. 3.19, 3.23) disclose the difference and relative importance of the two modes. For the biennial-ENSO mode, the strongest correlation signals, and hence the highest impact, come from the monsoon trough, the LLJ and the upper level easterlies (Fig. 3.19a, b), all of which are directly connected with the summer monsoon over the Horn of Africa (Section 3.3.2). On the other hand, for the ENSO/low frequency mode (Fig. 3.23a, b), none of the strongest correlation/regression signals corresponds to the primary monsoon rain producing systems, except probably for the anomalous anticyclone south of Madagascar (Fig. 3.4a).

Furthermore, some of the correlations indicate a weakened monsoon flow corresponding to enhanced Ethiopian rainfall (e.g., northeasterly correlation vectors over northern Indian Ocean in Fig. 3.23a). Note also the absence of statistically significant correlations between rainfall and the zonal wind in the upper troposphere (one of the primary components of the monsoon, Fig. 3.6b) for the ENSO/low frequency mode (Fig. 3.23b). If the ENSO phenomena were to influence the summer rains as severely as experienced in Ethiopia, we expect the 3.1-6.8-yr ENSO effects to be reflected in the primary monsoon systems that directly affect rainfall. As will be made clear in later sections, the weak connection between rainfall and atmospheric variables at the 3.1-6.8-yr band is largely a result of including May and October rainfall in the seasonal time series. It suffices to state here that the effect of ENSO on June-September rainfall is opposite to its effect during February-May and October-November. As a result, the opposing ENSO effects over the different portions of the time series may cancel out and flatten the correlation signals when May and October rainfall are included in the time series. This issue will be discussed in subsequent sections.

Remotely, the correlation between Ethiopian rainfall and the large-scale circulation over the eastern Indian Ocean and the Pacific at the 3.1-6.8-yr time-scale (Fig. 3.23) does not reflect the major ENSO characteristics identified for the biennial-ENSO mode (Fig. 3.19). In contrast to Fig. 3.19c and contrary to what is expected of a typical ENSO response, the correlations between rainfall and MSLP in Fig. 3.23c are weaker than the correlation values at the biennial-ENSO time-scale, and exhibit the same polarity over the eastern Pacific and southeastern Indian Ocean. In addition, the correlation vectors at the ENSO/low frequency time-scale (Fig. 3.23c) lack the typical ENSO signatures in the horizontal winds (strong easterly anomalies over equatorial central and eastern Pacific and westerly anomalies over eastern Indian Ocean corresponding to high rainfall events over Ethiopia) found for the biennial-ENSO mode (Fig. 3.19c). Note the strong northerlies west of the date line, the presence of westerly components in

the east of the date line, and the collapse of the anomalous anticyclone in the southern subtropical Pacific (Fig. 3.23c). As will be shown later in this chapter, these differences are the result of including May and October rainfall in the 5-day Ethiopian seasonal time series.

Analysis of the differences of composites of large-scale flow patterns associated with high and low rainfall phases shows that extratropical lows over western Europe/Mediterranean Sea and southern Atlantic Ocean positively affect rainfall (Figs. 3.24a). The northern hemisphere influence is noticeable in the negative geopotential height anomalies along the Red Sea and northern Arabian Sea. On the other hand, enhanced Ethiopian rainfall events are linked to the intensification of the Mascarene high southeast of Madagascar, where anomalous anticyclone and higher geopotential heights develop. At upper levels, the effect of extratropical westerlies is reflected in the cellular nature of the subtropical anticyclones and by the wedges of anomalous westerly troughs to the west and east of the Mediterranean (Fig. 3.24b).

# 3.3.6 Comparison of June-September and May-October Wavelet Spectra

The wavelet power spectrum for June-September 5-day average all-Ethiopian rainfall exhibits the primary features of the May-October spectrum discussed earlier. However, some additional features appear in the June-



Figure 3.24 Distributions of difference fields (corresponding to high minus low rainfall phases) between the composites of large-scale flow (vectors; m s<sup>-1</sup>)/height (shading; gpm) for time series wave band filtered at the 3.1-6.8-yr period: (**a**) 1000 hPa, and (**b**) 200 hPa. Rainfall anomaly thresholds are  $\pm$  0.5 mm d<sup>-1</sup> and correspond to about the top/bottom 1% of the time series. The reference vector is in m s<sup>-1</sup> (bottom right corner of each panel).

September spectrum (Fig. 3.25). First, a prominent and distinct peak appears in the 15-75-day band. Second, the separation of the variances at about 135 days becomes less distinct, leaving broadly distributed variance at sub-seasonal to seasonal bands. Third, only one dominant power emerges at the biennial-ENSO time-scale in the 1.4-3.1-year band. With the appearance of these distinct energy spikes, the variance associated with the annual cycle has decreased, contributing only about 13% of the total global variance at its peak. In addition to the 1.4-3.1-yr band, another 3.1-4.6-yr band appears in the June-September rainfall spectrum. Although the variance associated with this 3.1-4.6 year band is small,

the correlation patterns indicate clear ENSO signatures. This section reports the main results that emerged by restricting the analysis to June-September Ethiopian rainfall time series and highlights the effects of May and October in the seasonal time series.

In spite of the presence of a distinct sharp variance at short time-scales (Fig. 3.25 inset), rainfall variation in the 15-75-day band shows only a weak correlation with local moisture over Ethiopia, and no connection was found with the large-scale systems in the domain of analysis (not shown). In addition to the standard atmospheric variables (e.g., u, v, T, h, and p), a possible connection of rainfall variability at this mode with that of the MJO, local vertical wind shears, and vertical temperature lapse rates were investigated, but no satisfactory result was found. Hopefully, future research employing high resolution temporal and spatial scales would shed light on the physical processes associated with the June to September Horn of Africa rainfall variability at this time-scale.

In contrast to Sections 3.3.5.2 and 3.3.5.3, physically consistent and spatially coherent moderate-to-strong correlations were found between 5-day June-September Ethiopian rainfall and large-scale circulation patterns on the intraseasonal-to-seasonal time-scales (75-210 days). This difference is due entirely to the effects of including May and October in the previous analysis (Section 3.3.5). Figure 3.26 shows the correlation patterns for selected reanalysis fields



FIGURE 3.25. Global wavelet spectra of 5-day all-Ethiopian June-September rainfall (raingauge) for 1970-99. The amplitude is normalized by the total variance for the entire period. Insets magnify the major peaks at indicated time-scales.

and levels. Wet monsoon conditions are characterized by a southwest-northeast directed pressure gradient associated with a general pressure fall over the Arabian Peninsula and pressure rise over the Gulf of Guinea (Fig. 3.26a).

Consistent with this pressure gradient, westerly flow from the Atlantic increases the atmospheric moisture over the Horn of Africa and (Fig. 3.26b, c). This flow pattern becomes especially strong at 700 hPa (Fig. 3.26b). Inspection of the actual flow during wet events reveals enhanced wind confluence between westerlies and northerlies along the Red Sea and over Ethiopia (not shown),



FIGURE 3.26. Spatial patterns of simultaneous correlations between 5-day June-September Ethiopian rainfall (raingauge) and reanalysis fields for time series waveband filtered at 75-210 day period. (a) MSLP (shading) and horizontal winds at 1000 hPa (vector); (b) zonal wind (shading) and horizontal winds at 700 hPa (vectors); (c) vertically integrated water vapor (shading) and horizontal winds at 600 hPa (vectors); and (d) geopotential height (shading) and horizontal winds at 150 hPa (vectors). Thick solid (dashed) lines enclose positive (negative) correlation values significant at the 99.9% confidence level according to a two-tailed Student's t-test for the shaded fields. Correlations between rainfall and horizontal winds are shown as vectors, with unit vector (bottom right inset in each panel) representing a correlation magnitude of 1.0.

where rainfall is maximally correlated with vertically integrated moisture and substantially correlated with the easterly jet (Fig. 3.26c, d). In addition to the deepening of the heat low over the Arabian Peninsula, strong anticyclones that develop over the Mediterranean/north Africa and southern Indian Ocean (south of Madagascar) appear to enhance inter-hemispheric meridional flows and convergence (not shown).

On the 1.4-3.1 year time-scale, the atmospheric forcing associated with Ethiopian June-September rainfall is stronger than that of May-October rainfall. In agreement with the 1.4-3.1-yr mode of May-October rainfall, the largest circulation anomalies occur over the monsoon and subtropical regions (Fig. 3.27). In general, wet June-September events are associated with the development of anomalous cyclonic (anticyclonic) circulation over the southeastern Indian Ocean (northeastern Atlantic/western Mediterranean) and negative pressure anomalies over the Arabian Peninsula at low levels (Fig. 3.27a). At upper levels, the intrusion of anomalous westerly trough appears to split the subtropical anticyclone into two centers over the central Mediterranean and Pakistan, where geopotential height maximally positively correlates with rainfall at the biennial time-scale (Fig. 3.27b). The overall 150 hPa atmospheric flow for the 1.5-3.1 year cycle is very similar for the May-October and June-September time series – both time series feature anomalous subtropical anticyclones across the Mediterranean latitude and strong easterlies over the equatorial belt (Figs. 3.19b, 3.27b). Note,



FIGURE 3.27. Results of regression (vector) and correlation (shading) analyses of 5-day June-September time series wave band filtered for the 1.5-3.1 year period. (**a**) Correlation between MSLP and rainfall (shading) and regression of horizontal winds onto rainfall (vector) at 1000 hPa. (**b**) Correlation between geopotential height and rainfall (shading) and regression of horizontal winds onto rainfall (vector) at 150 hPa. Thick solid (dashed) lines enclose positive (negative) correlation values significant at the 99.9% confidence level according to a two-tailed Student's t-test for the shaded fields. The reference vector is in m s<sup>-1</sup> (bottom right corner of each panel).

however, the strong atmospheric forcing for the June-September time series, as reflected in the magnitudes of the correlation values and regression vectors (Fig. 3.27).

Moreover, unlike the case of May-October wavelet analysis, where many of the strongest rainfall anomalies for the biennial mode occur mainly in the beginning or ending months of the season (i.e., May and October, respectively), the strongest anomalies for the June-September wavelet analysis occur primarily during the peak of the season in July-August. The strongest negative (positive) anomalous July-August signals occurred in 1984, 1987, and 1997 (1988 and 1996), which clearly correspond to the dry and wet Ethiopian years, respectively.

The most pronounced difference between the May-October and June-September time series is observed at the ENSO time-scale. It was noted that at the 3.1-6.8-yr time-scale the May-October time series does not show the major ENSO characteristics (Fig. 3.23) in the wind and pressure fields because of the inclusion of May and October rainfall. In contrast to the May-October time series, the wavelet analysis for June-September reveals the classical ENSO signals in the Pacific and eastern Indian Ocean circulation patterns corresponding to the 3.1-4.6 year ENSO mode (Fig. 3.28). At the ENSO time-scale, June-September Ethiopian rainfall is negatively correlated with MSLP over Ethiopia, the Red Sea, and the Arabian Peninsula (Fig. 3.28a). The positive correlations between rainfall and MSLP over the southwestern Indian Ocean, northern Atlantic, and northern Africa indicate that the intensification of the Mascarene high in the south and the Azores/Saharan high in the north enhance Ethiopian rainfall (Fig. 3.28a). In the upper troposphere, the regression vectors depict strong easterlies across much of the tropics, where geopotential height correlates strongly negatively with rainfall (Fig. 3.28b).



FIGURE 3.28. Maps of regression and correlation analyses of 5-day June-September time series filtered for the 3.1-4.6-yr cycle. (**a**) Correlation between MSLP and rainfall (shading) and regression of horizontal winds onto rainfall (vector) at 1000 hPa. (**b**) Correlation between geopotential height and rainfall (shading) and regression of horizontal winds onto rainfall (vectors) at 150 hPa. (**c**) Same as (a) but the analysis is extended eastward into the tropical Indian and Pacific oceans. Thick solid (dashed) lines enclose positive (negative) correlation values significant at the 99.9% confidence level according to a two-tailed Student's t-test for the shaded fields. The reference vector is in m s<sup>-1</sup> (bottom right corner of each panel).

In the Pacific and the Indian Ocean, the regression vectors and the correlation between rainfall and MSLP exhibit the major ENSO signatures in the

wind and pressure fields, featuring the dipole pattern of the SOI (in the MSLP correlation field), and the anomalous westerlies in the eastern Indian Ocean and anomalous easterlies in the central and eastern Pacific at low levels (Fig. 3.28c). Note the clear differences between the flow patterns for June-September (Fig. 3.23) and those found for the May-October time series (Fig. 3.19c). Thus, ENSO affects Ethiopian rainfall by modulating the major monsoon systems during June-September. The lack of strong correlations between May-October Ethiopian rainfall and the major large-scale monsoon systems at the ENSO time-scale in Section 3.3.5.6 is due to the inclusion of May and October rainfall in the seasonal time series.

In summary, the dominant modes of variability associated with the June-September rainfall bear strong resemblance to that associated with the May-October rainfall, but the modes corresponding to June-September rainfall more strongly reflect the variability associated with core monsoon features. Except for the shorter scale mode of variability (<75 days), the filtered time series strongly correlates with identically filtered large-scale systems for all the other modes of variability. In particular, the variability of the annual cycle can be predicted to a very high degree of certainty.

On the other hand, there is no strong statistical connection between rainfall variability and the large-scale systems in the 15-75-day band. The variability

appears to be random for many of the atmospheric state variables and for some derived quantities that reflect atmospheric instabilities. Fortunately, except for few instances, the amplitudes of the 15-75 day filtered time series are not very large, and in most cases are smaller than those filtered on the annual cycle. It is likely that improving the spatial and temporal resolutions of the data used (e.g., using daily average rainfall for highly correlated neighboring stations and daily high-resolution atmospheric data) will help to identify the atmospheric forcing that affects June-September rainfall variability at the 15-75 day time-scale. Because the procedure is computationally very expensive, this may require reducing the domain of the large-scale systems.

All the discussion in the above sections considered the association of rainfall with atmospheric variables. However, to understand climate fluctuations and develop prediction models with long lead-time, the association of rainfall with slowly evolving boundary conditions needs to be studied. Because SST forcing is one of the most important boundary conditions influencing atmospheric seasonal variability (e.g., Charney and Shukla 1981; Kawamura 1998; Barnston et al. 2005), the connection between rainfall and global SST will be examined in the next section.

## 3.4 Rainfall and Global Sea Surface Temperature

Variations in SSTs are linked to rainfall variability over many parts of Africa (e.g., Lamb 1978; Folland et al. 1991; Ward 1998; Hastenrath et al. 1995). Barnston et al. (1996) demonstrated that the time-space behavior of the SST field alone influences the seasonal precipitation in certain seasons/regions of Africa, both on interannual and interdecadal time-scales. For Ethiopia, Segele and Lamb (2005) examined the possible associations of the onset, cessation, and growing length of the main rainy season for the most drought-prone region of Ethiopia with ENSO and global SST and found strong links between the commencement of the season and its duration with Indian Ocean and equatorial Pacific SSTs (r  $\sim$  +0.45 to +0.55). Gissila et al. (2004) also used global SSTs to predict June-September Ethiopian rainfall and found significant associations between Indian and Pacific SSTs and summer Ethiopian rainfall ( $\mathbf{r} \sim +0.6$ ). Here, we will examine the link between Ethiopian rainfall and global SST in detail using wavelet analysis. The analysis will be performed on a monthly basis to match the temporal resolution of the HadISST1 global SSTs that were used. To clarify further the differences regarding the effects of ENSO on May-October and June-September rainfall noted in Sections 3.3.5.5 and 3.3.5.6, the analysis in this section will include the spring season. Thus, February-May, June-September, and January-December rainfall time series will be analyzed.

June-September (JJAS) is the primary rainy season ("Kiremt") for about twothirds of Ethiopia and accounts for more than 60% of the annual total rainfall (e.g., Fig. 1a of Segele and Lamb 2005). On the other hand, mid-February to mid-May, the main rainy season for southern Ethiopia, is a secondary rainy season ("Belg") for the Main Rift Valley and the surrounding regions, including southwestern, central, eastern, and northeastern Ethiopia. Although the contribution of the Belg rains to the annual rainfall total is small, it is crucial for some of northern Ethiopian highlands that largely depend on the short rains for cultivation (e.g., Broad and Agrawala 2000). Figure 3 of Segele and Lamb (2005) provides examples of the temporal distributions of the two seasons for different parts of Ethiopia. The current approach employed in this section builds on earlier study of Segele and Lamb (2005) and offers further evidence linking SST and Ethiopian rainfall at different time-scales.

Figure 3.29 shows the average wavelet spectra for the annual and boreal spring and summer monthly rainfall totals for 1970-99. The major differences among the three time series are the relative importance of the annual cycle, the absence of significant power at the seasonal time-scale in the summer wavelet spectrum, and the large distinct peaks in the seasonal and biennial modes for the February-May (FMAM) time series. Clearly, the seasonal and biennial peaks in the spring rains must have modulated the power distribution for the May-

October rainfall (Fig. 3.11c); note the weak seasonal peak and the shift in the biennial power for JJAS time series (Figs. 3.25, 3.29).



FIGURE 3.29. Average wavelet spectra of monthly total all-Ethiopian rainfall (raingauge) for 1970-99. The wavelet analysis was performed on spatially averaged monthly rainfall totals for February-May (blue), June-September (green), and January-December (red). The amplitude is normalized by the total variance for the entire period for each spectrum.

The frequency (period) limits of the spectral bands for the three time series in Fig. 3.29 slightly differ from each other, but each time series will be divided into 5 spectral bands—seasonal, annual, biennial, ENSO, and low frequency modes (Table 3.1). Note that we have separated the biennial and ENSO modes because they are distinct here. Note also that because of the monthly temporal resolution of the data, the power at the intraseasonal time-scale is very small. Thus, the lowest time-scale identified is seasonal. In the following sections, the linkage between global SST and rainfall will be explored using February-May, June-September, and January-December monthly rainfall time series.

		Period	
Mode	FebMay	JunSept.	JanDec.
Seasonal	< 250 days	< 235 days	< 235 days
Annual	250 days-1.46yrs	235 days-1.46 yrs	235 days-1.47 yrs
Biennial	1.46-2.92 yrs	1.46-3.1 yrs	1.47-2.57 yrs
ENSO	2.92-4.43yrs	3.1-4.43yrs	2.57-4.47 yrs
Low-frequency	> 4.43 yrs	> 4.43 yrs	> 4.47 yrs

Table 3.1. Spectral bands used for the decomposition of rainfall and SST time series.

#### 3.4.1 Seasonal Variability

The short rains exhibit strong associations with global SST with distinct hemispheric contrasts on seasonal time-scale (Fig. 3.30a). Warm (cold) SST anomalies in the northern (southern) hemisphere enhance (weaken) FMAM rains. The strength of the association is remarkably high, with strong positive correlation of about 0.87 over the northern Arabian Sea and South China Sea, and negative correlation of -0.89 over southeastern Indian Ocean and southern Pacific. The spatial homogeneity of the strong correlations also is very high. Clearly, these strong correlations indicate a high predictability potential for FMAM seasonal rainfall.



 $-1 \quad -0.9 \quad -0.8 \quad -0.7 \quad -0.6 \quad -0.5 \quad -0.4 \quad -0.3 \quad -0.2 \quad -0.1 \quad 0.1 \quad 0.2 \quad 0.3 \quad 0.4 \quad 0.5 \quad 0.6 \quad 0.7 \quad 0.8 \quad 0.9 \quad 1 \quad 0.6 \quad 0.7 \quad 0.8 \quad 0.9 \quad 0.9 \quad 0.8 \quad 0.9 \quad 0.9 \quad 0.8 \quad 0.9 \quad 0.9$ 

FIGURE 3.30. Spatial patterns of February-May concurrent correlations between all-Ethiopian rainfall and SST waveband filtered at the seasonal time-scale (30-250 day) for 1970-99. The correlation analysis was performed on monthly rainfall totals for February-May, and uses 120 data pairs at each grid point. Thick solid (dashed) lines enclose positive (negative) correlation values significant at the 99.9% confidence level according to a two-tailed Student's t-test. (b) Same as (a) except for June-September. (c) Same as (a) except for January-December. The correlation map in (c) is constructed based on 360 data pairs at each grid point.

For JJAS (Fig. 3.30b), the correlation magnitudes are not as strong as for the FMAM rains, consistent with the weak and less distinct peak in the wavelet power spectrum at the seasonal time-scale (Fig. 3.29). The polarities of the correlations are the same as for FMAM over much of the Southern Hemisphere, the northern Atlantic and northern Pacific. SSTs in the Mediterranean Sea also correlate positively with JJAS rainfall. However, JJAS rainfall correlates weakly negatively with SST over the Arabian Sea, which is a marked charge from FMAM (Fig. 3.30a, b). The southern Indian Ocean and the southeastern Pacific, on the other hand, show relatively strong negative correlations (-0.3 to -0.6) between Ethiopian rainfall and SST over a large area (Fig. 3.30b).

The correlation patterns for the annual time series (Fig. 3.30c) exhibit many of the features of the FMAM patterns but appear to be affected by variability in October-December. The strong negative correlations over the Arabian Sea and over south China/Philippine Sea are opposite to the strong positive correlations that exist for the FMAM time series. SST variations in the equatorial Atlantic (10°S-10N°) also strongly negatively correlate with the annual Ethiopian rainfall time series. The negative correlations over the southern hemisphere oceans, present in both FMAM and JJAS correlation maps, are replaced by weak positive correlations in the January-December map. The annual correlation map also exhibits stronger positive correlations in the North Pacific and North Atlantic than in Fig. 3.30b.

#### 3.4.2 Annual Variability

The above correlation patterns observed for the seasonal cycle persist in the annual cycle, although the magnitudes of the correlation slightly weaken for the short rains (FMAM). During FMAM, the strongest positive correlations are located over the Arabian Sea and the South China Sea while strong negative correlation values cover much of the southern hemisphere oceans (Fig. 3.31a).

The strong positive correlations over the northern Arabian Sea at both the seasonal and annual cycles in FMAM are likely indications of the positive contribution of a warm moisture flux into the Horn of Africa and, at times, the positive influence of westward propagating tropical disturbances/storms. The warm waters over the Arabian Sea serve as the main moisture source for the spring rains over the Horn of Africa. As the Arabian anticyclone/ridge moves into the water (e.g., Ju and Slingo 1995), the easterly/northeasterly trades cross a long trajectory across the warm waters and increase moisture over Ethiopia. Climatologically, the eastward shift of the Arabian anticyclone usually follows the passage of midlatitude frontal systems across the Mediterranean Sea. These frontal lows extend upper level troughs southward into the Horn of Africa as they cross the eastern Mediterranean, and interact with the nearby ITCZ in southern Ethiopia during FMAM. This interaction creates extended southwestnortheast oriented cloud mass along the Main Rift Valley in the presence of warm moist air from the Arabian Sea.



FIGURE 3.31. Same as Fig. 3.30 except for the annual time-scale.

Compared to the seasonal cycle, the correlation patterns at the annual timescale show strong correlation fields and high spatial homogeneity for JJAS (Fig. 3.31b). The strongest and more coherent correlation signals between rainfall and SST occur over the northern Pacific, northern Atlantic, and over western Indian Ocean. The negative correlation over the western Indian Ocean, which also is present for the seasonal cycle, suggests that stronger monsoons are favored by cold waters off the coast of Somalia and over northern Arabian Sea. A similar negative correlation pattern has been found between Indian rainfall and SSTs over western Indian Ocean in JJAS (e.g., Rao and Goswami 1988), and its existence is ascribed to dynamic response of the ocean to wind forcing and/or surface heat exchanges (e.g., Ju and Slingo 1995; Kawamura 1998).

The correlation patterns for the January-December time series appear largely to be a linear combination of the spring and summer conditions, and involve sharp hemispheric correlation contrasts and strong positive correlations over South China Sea (Fig. 3.31c). In general, the correlation maps exhibit robust temporal and spatial consistency in the three correlation maps for the annual cycle. In particular, the positive (negative) correlations over the northern (southern) Pacific and the northern (southern) Atlantic persist in the seasonal and annual correlation maps, and remain strong especially for the FMAM and January-December time series.

### 3.4.3 Biennial Variability

Differences between the correlation patterns for the spring and summer rains begin to show at the longer time-scales. For the biennial mode (Fig. 3.32a), a sharp difference in correlation patterns appears over the equatorial Pacific. The

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FIGURE 3.32. Same as Fig. 3.30 except for the biennial variability.

short rains (FMAM) exhibit modest positive correlations over eastern equatorial Pacific and negative correlations over the western portions. In contrast, JJAS rainfall correlates strongly negatively with SSTs over eastern and central equatorial Pacific, with positive correlations covering parts of equatorial western Pacific (Fig. 3.32b). In both cases, the correlation patterns possess clear ENSO signatures, with a region of strong correlation coinciding with the tongue of anomalous SST in the eastern Pacific that typically occurs during ENSO events, and a region of the opposite correlation over the western Pacific forming a horseshoe pattern that extends into both hemispheres. Although not as distinct, another difference between the FMAM and JJAS occurs over the Indian Ocean, with positive (negative) correlations between FMAM (JJAS) rainfall and SSTs over southeast Indian Ocean/western Indian Ocean. It is clear that a warm tropical Pacific tends to enhance (weaken) the spring (summer) rains over Ethiopia at the biennial time-scale.

Because of the opposite effects of SSTs on the spring and summer rains, there are no significant correlation signals in the annual correlation map over the Pacific (Fig. 3.32c). The positive correlations over the western Indian Ocean for the annual time series are partially the result of the positive association of the spring rains with SST over the western Indian Ocean (Fig. 3.32a), as well as the positive correlation of the summer rains with SST over the central Indian Ocean (Fig. 3.32b) at the biennial time-scale. However, an additional contribution must have come from the October-December rains, possibly through a positive contribution arising from warmer SSTs and enhanced tropical disturbances over the northern Indian Ocean. Climatologically, tropical disturbances form over the warm seasonal waters in the Indian Ocean in October-November, and in some years, move into the Horn of Africa and prolong the monsoon season there (e.g., Segele and Lamb 2005). This may offset the negative correlations over western Indian Ocean in summer.

## 3.4.4 Variability on ENSO Time-Scale

Clear ENSO signatures appear in the correlation maps for the 3-4-year waveband filtered time series (Fig. 3.33), especially for JJAS. Although no statistically significant correlation exists over the eastern equatorial Pacific, the short rains exhibit isolated positive correlations with SSTs over the central equatorial Pacific, which appear to extend from a region of strong positive correlation over northeastern Pacific (Fig. 3.33a). In contrast to the correlation patterns for the biennial mode, SSTs over much of northern and southeastern Indian Ocean correlate strongly negatively with the short rains, whereas the southwestern Indian Ocean strongly positively correlate with FMAM rainfall. Thus, the effects of the equatorial Pacific on the short rains are stronger at the biennial time-scale while the Indian Ocean appears to be important during ENSO episodes.

During JJAS, SSTs over the Pacific correlate strongly with JJAS rainfall. Strong negative correlations cover a large region of the central and eastern equatorial Pacific and bands of positive correlations oriented southeastnorthwest and southwest-northeast span the southern and northern Pacific,

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FIGURE 3.33. Same as Fig. 3.30 except for the ENSO mode.

respectively. The spatial structure of the correlation field bears a close resemblance to SST anomalous composite structure during the mature and transition phases of El Niño (e.g., Rasmusson and Carpenter 1982; Wang 1995). Equally strong association is found for the Indian Ocean where SSTs correlate negatively with rainfall, with the strongest correlation over the northern Indian Ocean. Inspection of the filtered data revealed that SST anomalies over the northern Indian Ocean and central and eastern equatorial Pacific have the same polarity (not shown). The correlation between the two attains a maximum of +0.8 at 3 months lag. This is consistent with previous studies, which indicated that a significant fraction of SST variability over the Indian Ocean is related to ENSO and, in particular, that SST anomalies over Indian Ocean tend to be in phase with those in the central and eastern Pacific (e.g., Kawamura 1998; Baquero-Bernal et al. 2002; Lau et al. 2005; Terray and Dominiak 2005). Klein et al. (1999) noted that SST anomalies in the Indian Ocean lag those in the Pacific by about 3 months. Furthermore, Ju and Slingo (1995), Meehl (1997), and Kuwamura (1998), among others, have shown that the Indian Ocean SST anomalies tend to become positive when the Asian summer monsoon is weak.

The annual correlation map primarily reflects the correlation patterns for FMAM and JJAS or a combination of them (Fig. 3.33c) over most ocean basins. However, strong negative correlations appear over the southeastern Indian Ocean west of Australia. These correlation values are stronger than the seasonal correlations for the FMAM and JJAS time series. The southwestern Indian Ocean also features strong positive correlation signals. It is not clear at this time if and how the SST distribution over the southern Indian Ocean is related to the October-November rainfall time series.

#### 3.4.5 Low-Frequency Variability

The strongest signals for low frequency variability are associated with the short rains (Fig. 3.34). The northern Pacific and the Indian Ocean exhibit strong and spatially homogeneous correlations during FMAM (Fig. 3.34a). While positive correlations dominate the Indian Ocean, opposite polarities of very strong correlations cover the northern Pacific, especially east of the dateline in FMAM. The well-defined correlation structure in the northeastern Pacific suggests the presence of longer time-scale variability, but a thorough investigation of the link between Ethiopian short rains and SST variability in the northern Pacific on decadal and longer time-scales is left for future studies.

During summer, low-frequency variability over isolated areas in the Pacific and western Indian Ocean appears to affect Ethiopian rainfall variability (Fig. 3.34b), but the magnitudes and spatial extent of the correlations are much more reduced compared to the corresponding signals for FMAM. In addition, most of the strong low-frequency associations between summer rainfall and SST come from the subtropical and higher latitude oceans. The correlation patterns for the annual time series resemble those for FMAM, but the strong correlations over the northern Pacific for FMAM have diminished substantially for the annual time series (Fig. 3.34c). In contrast, the correlation signals over the Indian Ocean, the equatorial Pacific, and the northern Atlantic have markedly increased for the annual time series compared to the correlations for FMAM in Fig. 3.34a. In general, low frequency variability associated with SST variations over the Indian Ocean, as well as over the subtropical ocean basins in the Pacific and the Atlantic appear to exert strong influence on (especially) the non-monsoon Ethiopian rains.



FIGURE 3.34. Same as Fig. 3.30 except for the low-frequency variability.

# 3.5 Summary

This chapter investigated the physical characteristics of monsoon variability over the Horn of Africa and identified the atmospheric and oceanic features associated with rainfall variability on several key time-scales. At the intraseasonal time-scale, Ethiopian rainfall variability largely is determined by local moisture availability and dynamics. For May-October rainfall time series, atmospheric circulation patterns occurring at time-scales shorter than a season appear to weaken the major monsoon features. On seasonal and longer timescales, regional and remote large-scale circulation features and global SST forcing become important. At the seasonal time-scale, circulation patterns over the Arabian Peninsula, the Atlantic Ocean, and the Mediterranean Sea are the major atmospheric monsoon components that affect Horn of Africa summer rainfall. In addition, a strong oceanic forcing is observed over the southern Indian Ocean, in which cooler SSTs favor enhanced Ethiopian JJAS rainfall. Very strong correlations of opposite polarity covering the Northern and Southern hemispheres intimately link global SST and Ethiopian short rains at the seasonal time-scale. The presence of very strong seasonal to annual correlation signals in wave banded global SST and rainfall indicates a high predictability potential for the Ethiopian short rains.

The annual cycle reflects the long-term climatological characteristics of the monsoon, and features the classical monsoon components that maximally affect

Horn of Africa rainfall. This mode is strongly affected by oceanic forcing over the western Indian, northern Atlantic, and tropical Pacific Oceans, where cooler waters off the eastern coasts of Africa and the Arabian Peninsula and warmer waters in the East China Sea and off the southeastern coasts of North America enhance Ethiopian rainfall. On the biennial-to-ENSO time-scales, the equatorial Pacific and the Indian Ocean exert strong influence on rainfall by modulating regional circulation systems. Strong anomalies associated with the biennial-to-ENSO variability appear in the monsoon trough, the Mascarene high, the Azores/Saharan high, and the TEJ and the associated upper tropospheric systems, but only weakly affect the St. Helena high. It is especially interesting to note that SST variations in the equatorial and eastern portions of the southern tropical Atlantic are correlated positively, albeit weakly, with Ethiopian IJAS rainfall at the ENSO time-scale. This indicates that SST variations in the above areas of the Atlantic tend to counteract the effects of ENSO-related SST variations in the equatorial Pacific on Ethiopian JJAS rainfall.

On the decadal and longer time-scales, SST variations in the western Indian, northeastern Pacific, and southern Atlantic Oceans tend to have strong influence on summer rainfall. However, longer time-scale SST fluctuations over the Indian Ocean and especially over the northeastern Pacific appear to affect the short rains more strongly than Ethiopian monsoonal rainfall. The presence of such strong correlations between FMAM rainfall and global SST nearly for all
time-scales indicates a high predictability potential for the Ethiopian short rains. In general, this study has enormously enhanced our knowledge of the regional and local circulation features and mechanisms that produce the rainfall variability. How this improved knowledge base can be translated into the development of a reliable and accurate statistical prediction model is the focus of the next chapter.

# CHAPTER 4: PREDICTABILITY OF ETHIOPIAN RAINFALL

# 4.1 Preamble

Rainfall is one of the most important climate elements that affects the livelihood and wellbeing of the majority of Ethiopians. In addition to the inherent large spatial and temporal rainfall variability arising from the tropical location, the complex rugged Ethiopian mountains further complicate the spacetime distribution. Due to the geographic location, latitudinal range, and complex orography, most parts of the country (approximately the northern two-thirds) experience one dry season from October to January (locally known as Bega), and two nearly consecutive wet seasons separated only by a few weeks—one from mid-February to mid-May (locally known as *Belg*), and the other from June to September, which is locally known as Kiremt (e.g., Degefu 1987). Although June-September usually is taken as the period of the main rainy season, this categorization is most valid for central and parts of northern Ethiopia. Segele and Lamb (2005) have shown that the main rains start early in March over southwestern Ethiopia, in May over the western and northwestern regions, and in July over northern/northeastern Ethiopia. However, the southern one-third of the nation, which covers the southern and southeastern lowlands, has the typical equatorial East African dry-wet seasons, with the long intermittent rains

concentrating during March-May and the short rains occurring during September or October-November.

The timing and spatial distribution of the agriculturally and hydrologically important Belg and Kiremt rains, which are caused by different atmospheric circulation mechanisms, overlap in parts of the country. For example, while the Belg rains are winding down over the central and northeastern Ethiopia, the Kiremt rains pick up in intensity and widen their spatial coverage over southwestern, western, and northwestern Ethiopia (e.g., Segele and Lamb 2005). This situation further complicates the understanding of rainfall variability in the region. Because Kiremt is the main rainy season in which about 85-95% of the country's food crop is produced (e.g., Degefu 1987), the entire agricultural activities and production of the nation hinge on the amount and distribution of rainfall during that season.

Over the years, the need for the understanding and skillful predictions of weather and climate have heightened in Ethiopia, due primarily to the frequent droughts and floods that hit the nation. However, only a few studies have attempted to develop quantitative rainfall forecasting models for Ethiopia on seasonal time-scales (e.g., Gissila et al. 2004; Korecha and Barnston 2006). Also, to our knowledge, as yet there has not been an attempt to develop statistical models for medium-range weather forecasting. To date, the use of empirical prediction models for short to long range rainfall forecasting in Ethiopia is in its infancy. To understand better and predict the Ethiopian rainfall variability from days to months in advance, a detailed and physically based approach will be employed in this study.

For empirical predictions of the Indian monsoon, Hastenrath et al. (1995) underlined the importance of diagnostic studies of the atmospheric circulation for the identification of potential predictors (climate system variables) for prognostic applications. Webster and Hoyos (2004) also noted that a key aspect of a physically based empirical regression scheme is the choice of a set of predictors. Such predictors then are utilized to develop a regression model for the so-called "training period", which usually coincides with the early portions of the data records. A critical part of the regression scheme is the subsequent evaluation of the predictions using independent data (Hastenrath et al. 1995; Webster et al. 1998). Hastenrath (1986) suggested considerable prospects for rainfall prediction by such forecasting schemes because they combine extensive diagnostic investigations into the interannual circulation and climate variability with statistical methods.

Webster and Hoyos (2004) used a new type of statistical model for the prediction of intraseasonal oscillations of the south Asian monsoon. The technique combines wavelet analysis and linear regression. This novel approach will be utilized here to develop empirical models to forecast rainfall over Ethiopia at medium (a week to less than a month) and long range (a month to seasons) time-scales. In the spirit of Hastenrath (Hastenrath et al. 1995), the comprehensive investigation of Chapter 3 already has provided many potential predictors that are physically and statistically linked to rainfall variability over the Horn of Africa.

# 4.2 Data and Methodology

## 4.2.1 Data

To develop medium and long range rainfall prediction models, several sets of rainfall data will be used--spatially averaged 5-day June-September all-Ethiopian rainfall, monthly January-December all-Ethiopian rainfall, and monthly rainfall for individual selected stations. In addition, the model development employs the NCEP-NCAR reanalysis and the UK Meteorological Office Hadley Centre's sea surface temperature (SST) data sets. These data sets were already described in previous chapters.

## 4.2.2 Methodology

The wavelet banding technique of Webster and Hoyos (2004) combines wavelet analysis and linear regression. The details of the wavelet analysis technique were provided in Section 3.2. Before performing linear regression, a common wavelet banding technique is applied to the predictand (rainfall) and to the predictors that are chosen from detailed diagnostic studies. As shown in Section 3.2, wavelet banding sorts the time series into specific spectral bands. Webster and Hoyos (2004) noted that the isolation of spectral bands is the key factor in the wavelet banding statistical scheme because it allows the regression tool to identify, independently in each band, the existing relationship between the predictand and predictors. To forecast the predictand at a future time, the regression scheme will be applied for each spectral band using only the state of the system available at the time of the forecast. At the end of the process, the bands are combined to provide the total forecast values of the predictand.

As an alternative to traditional linear regression analysis, artificial neural networks have been used for rainfall predictions. A neural network (NN) is a powerful nonparametric statistical tool that can model physical relationships with any degree of nonlinearity (e.g., Hastenrath et al. 1995; Hall et al. 1999; McClelland and Rumelhart 1988, pp. 128-137; Robinson 1991). A neural network is trained with a large representative data set, which then is used to predict output values from a new set of input variables. For this study, neural network freeware developed by Dr. B. Fiedler (University of Oklahoma, Norman), downloaded from the website <a href="http://mensch.org/neural/nnet.tar.gz">http://mensch.org/neural/nnet.tar.gz</a>) was utilized. This NN is a popular feedforward network in which the free parameters gradually are adjusted by a back propagation algorithm. Details of the network are discussed in Dean and Fiedler (2002).

To identify the coherent modes of variability associated with Horn of Africa rainfall, wavelet analysis was performed on several atmospheric variables over a large domain. Using that analysis, we were able to identify atmospheric and oceanic conditions that modulate rainfall in the region. In addition to selecting predictors through descriptive statistical analysis and physical reasoning, it was found valuable to use predictors covering the entire domain of interest. By applying a Singular Value Decomposition (SVD) technique as a data compression tool, the large number of original variables can be reduced to few essential variables that contain much of the large-scale variability. SVD expresses any matrix *X* as a product of three other matrices (e.g., Green and Carroll 1978, pp. 348):

$$X_{mxn} = U_{mxr} D_{rxr} V_{rxn} \tag{4.1}$$

where the ' denotes transpose,  $X_{mxn}$  is a general matrix of m rows of observations (time) by n columns of, say, spatial locations of variable X, U is the matrix of eigenvectors of XX', V is the matrix of eigenvectors of X'X, and D is a diagonal matrix of singular values. The rank of X is determined by the number of positive singular values, with  $r(X) \leq \min(m, n)$ . The SVD representation can be applied to any type of matrix—singular or nonsingular, square or rectangular. Note that when the spatial locations are represented by the columns, the matrix operation X'X eliminates the temporal dimension,

leaving a measure of the dispersion of the spatial structures across the sampling dimension. Under this representation, the matrix of Principal Component (PC) scores is F = UD = XV and a geographical plot of the columns of V gives a map of the PC loadings as distributed over the spatial extent of the data X (Richman 1986). The SVD technique is applied on wave band filtered atmospheric and oceanic variables, with the temporal means removed, to obtain the PCs. Because the PCs are uncorrelated, they are well-suited for regression analysis.

The spatial eigenvectors of the SVD technique applied to a data matrix *X* are identical to the eigenvectors obtained from the standard Empirical Orthogonal Function (EOF) analysis performed on correlation or covariance matrices of *X*. To illustrate the connection between the EOF and SVD technique, we can apply the EOF method on the correlation matrix  $R = \frac{1}{m-1}X'_SX_S$  of a standardized variable  $X_s$  as:

$$R = C\Lambda C', \tag{4.2}$$

where *C* and  $\Lambda$  are the eigenvalues and eigenvectors of the correlation matrix. Using Eqn. (4.1) for  $X_s$ , the correlation matrix can be expressed as

$$R = \frac{1}{m-1}(UDV')'(UDV') = \frac{1}{m-1}VD'(U'U)DV' = V\frac{D'D}{m-1}V',$$
(4.3)

where we invoked the symmetry of the correlation matrix and used the identity

I = U'U. Comparing Eqns. (4.2) and (4.3), we note that C = V and  $\Lambda = \frac{D}{m-1}$ . Thus, the eigenvectors are identical, but there is a factor of the "length of the time series minus one" between the eigenvalues of the correlation matrix and the singular values of the original data matrix (e.g., Green and Carroll 1978, pp. 359). In this study, we apply the term "EOF" to the spatial eigenvectors of a single field obtained through the SVD technique.

# 4.3 Prediction on Intraseasonal Time-Scales

In addition to monthly and seasonal climate forecasts, medium-range weather forecasts have significant societal importance. At the National Meteorological Services Agency of Ethiopia (NMSA), 10-day forecasts are issued to supplement the generalized monthly and seasonal outlooks that are disseminated every month and season. The user community requires these forecasts to be detailed, timely, and accurate. However, NMSA primarily relies on subjective assessments of numerical weather prediction (NWP) model output charts, obtained via the Global Telecommunication System (GTS), to provide 10day forecasts. Because these NWP outputs usually are valid for 5-8 days, the forecasters' personal judgments again play a central role in preparing 10-day forecasts. Such forecasts are not accurate and detailed enough to meet the needs of the user community. This section addresses these issues and develops a highly dependable medium-range prediction model that can be used to forecast rainfall from 5 to 25 days in advance.

For medium-range predictions, the diagnostic results of Chapter 3 were used. The spectrally filtered data were for the 5-day (pentad) average all-Ethiopian June-September rainfall time series for 1970-99 (Section 3.3.6). From the average wavelet spectra, seven wavelet bands were identified. These bands correspond to periods of less than 25 days, 25-75, 75-210 days, 210 days to 1.4 years, 1.4-3.1, 3.1-4.6, and > 4.6 years. To improve the statistical connection between rainfall and the various atmospheric variables at a shorter time-scale, we chose to divide the 15-75-day variability into two bands-15-25 days and 25-75 day periods. This categorization appears to have helped slightly in improving the forecast by preventing the high frequency variability from severely affecting the predictability of rainfall at longer intraseasonal periods. Various atmospheric variables from the surface to 100-hPa and covering Africa, the Mediterranean Sea, and parts of the Atlantic and Indian Oceans were identically wave banded for the analysis domain shown in Fig. 3.3a. Through extensive examination of the evolution of the atmospheric state variables and rainfall, time series of different predictors were extracted for each band that exhibit strong statistical and physical linkage with Ethiopian rainfall. Table 4.1 lists the selected predictors along with their levels and geographic locations.

No.	Period	Field	Region
1		Vertically integrated moisture	12.5°–20°N, 32.5°–40°E
		(Horn of Africa)	
2	Less than	Zonal wind at 700 hPa (West Africa)	10°–15°N, 10W°–10°E
3	25 days	Geopotential height at 850 hPa (West	20°–30°N, 10°W–0°E
		Africa)	
4		Vertical velocity at 500 hPa (Horn of	5°–10°N, 37.5°–45°E
		Africa)	
5		Vertically integrated moisture	7.5°–12.5°N, 32.5°–45°E
		(Horn of Africa)	
6		Geopotential height at 700 hPa (West	5°S–10°N, 10°W–0°E
	25-75 days	Africa)	
7		Zonal wind at 700 hPa (Horn of Africa)	2.5°–7.5°N, 30°–40°E
8		Meridional wind at 1000 hPa (Sudan)	5°–10°N, 20°–30°E
9		Vertically integrated moisture	7.5°–17.5°N, 40°–55°E
		(Horn of Africa)	
10		Geopotential height at 700 hPa (Horn of	10°–20°N, 40°–60°E
		Africa)	
11	75-210	Zonal wind at 700 hPa (East Africa)	0°–5°N, 30°–50°E
12	days	Meridional wind at 700 hPa (Horn of	10°–17.5°N, 37.5°–42.5°E
		Africa)	
13		Vertical velocity at 500 hPa (Horn of	5°–10°N, 37.5°–42.5°E
		Africa)	
14		Vertically integrated moisture (Northern	12.5°–17.5°N, 10W°–40°E
		Africa)	
15		Surface pressure (Northeast	25°–37.5°N, 25°–40°E
		Africa/Eastern Mediterranean)	
16	210 days	Zonal wind at 1000 hPa (Red Sea)	10°–20°N, 37.5°–50°E
17	to	Zonal wind at 150 hPa (Northern	15°–20°N, 15°–25°W
	1.4 yrs	Atlantic)	
18		Meridional wind at 850 hPa (northern	5°–12.5°N, 47.5°–60°E
		Arabian Sea)	
19		Vertical velocity at 500 hPa	10°–20°N, 40°–45°E
		(northeastern Ethiopia/Red Sea)	·

Table 4.1. Predictors used for intraseasonal prediction of all-Ethiopian June-September rainfall.

Table 4.1. Contd.					
20		Surface pressure (Arabian Peninsula)	20°-30°N, 42.5°-50°E		
21		Surface pressure (southeastern Indian	27.5°–32.5°S, 85°–95°E		
		Ocean)			
22		Zonal wind at 700 hPa (eastern equatorial Africa)	0°–5°N, 35°–50°E		
23	1.4-3.1	Zonal wind at 150 hPa (easterly jet)	5°–12.5°N, 50°–70°E		
24	yrs	Meridional wind at 150 hPa (easterly jet)	5°–15°N, 70°–80°E		
25		Temperature at 500 hPa (northeast Africa)	27.5°–32.5°N, 20°–30°E		
26		Geopotential height at 700 hPa (Yemen)	10°–15°N, 45°–55°E		
27		Surface pressure (Bay of Bengal)	10°-17.5°N, 85°-97.5°E		
28		Geopotential height at 700 hPa (Gulf of Eden)	10°–15°N, 40°–50°E		
29	3.1-4.6	Zonal wind at 500 hPa (Oman)	20°-25°S, 47.5°-60°E,		
30	yrs	Meridional wind at 500 hPa (southeast Atlantic)	32.5°–37.5°S, 10°–25°E		
31		Temperature at 200 hPa (Gulf of Guinea)	10°S–10°N, 20°W–10°E		
32		Surface pressure (Southern Atlantic Ocean)	22.5°-30°S, 15°W-0°		
33		Temperature at 150 hPa (Pakistan)	30°–35°N, 55°–70°E		
34	> 4.6 yrs	Temperature at 200 hPa (southeast Indian Ocean)	22.5°–27.5°S, 72.5°–85°E		
35		Zonal wind at 700 hPa (northern Arabian Sea)	10°–15°N, 65°–80°E		
36		Meridional wind at 500 hPa (Gulf of Guinea)	5°S–0°, 10°W–0°		

# 4.3.1 Least Squares Linear Regression Prediction

For each wave band, a linear regression equation was developed for different lags. For example, beginning at the current time t, to forecast the future value of rainfall (R) n pentads after the current time R(t+n), the predictors  $X_j$  are lagged by n positions in time, where the subscript j denotes the various predictors for each band (Table 4.1). Thus, the data used to fit the predictand are from R(n+1),

R(n+2),..., R(t), and X<sub>j</sub>(1), X<sub>j</sub>(2),..., X<sub>j</sub>(t-n). For each wave band a regression equation of the form:

$$R = b_1 X_1 + b_2 X_2 + \dots + b_j X_j, \tag{4.4}$$

was fitted. Note that because the wavelet analysis removes the mean of the time series, there is no need to add an intercept. Although, the predictors were selected based on their strong statistical and physical connections with rainfall, for each band only those predictors that showed large F values (significant at 1% level) were retained in the final regression equation. The performance of the model was tested using the cross-validation method (e.g., Wilks 1995, pp. 194) and also by splitting the time series into two subsets and reserving one subset for verification (e.g., Hastenrath et al. 1995; Webster et al. 1998). For the cross validation method, the model was fitted on all years excluding a moving single year that was used to validate the model. The procedure was repeated until each year was used once as the validation data. For the second method, also known as retroactive validation method (e.g., Barnston et al. 1994), throughout this study we used 1970-89 for model development and 1990-99 for verification.

For both cases, the regression equations do not perform well on the intraseasonal and seasonal time-scales, yielding very low correlations between predicted and observed rainfall; even for the training period, the correlation magnitudes are modest and range from 0.2-0.35. Fortunately, the amplitudes of

the time series in these bands are not very large and thus do not significantly affect the overall rainfall forecasts.

On the other hand, all wave banded time series at longer time-scales (annual and longer) exhibit exceptionally strong correlations between observed and predicted rainfall. A sample of the model performance is given in Table 4.2. Note the very high degree of correlation between the modeled and observed rainfall as indicated by R<sup>2</sup>. The adjusted R<sup>2</sup>, adjusted for the number of predictor variables, is also very high. As can be seen from the table, only the predictors with near zero probability of F-Values were retained. Thus, the probability that all the regression coefficients are zero is extremely small (~0). A two-sided t-test also gave negligible probability of obtaining the estimated values of the coefficients if the actual parameter values are zero.

Figure 4.1a shows the observed and predicted time series for a 10-day forecast for the retroactive validation method. The correlation between the two time series is high (0.79, significant at 1% level). The evolution of the predicted values generally agrees with the observed patterns; the peaks and valleys are forecast with high degree of accuracy. Although the model clearly reproduces the longer time-scale variability (annual and above) to a very considerable degree of accuracy, the high frequency variability is still not very well represented. The magnitudes of the peaks also are underestimated, especially in Table 4.2. Analysis of variance and regression summary for selected wave bands with very high degree of model fitness for a 10-day forecast based on 1970-99. The column headings df, SS, MS, and SE stand for degrees of freedom, sum of squares, mean square, and standard error, respectively.  $R^2$  is the coefficient of multiple determination and measures the proportion of the variation in rainfall that is accounted for by the best linear composites of the predictors. The number entries under the *Source/Variable* column refer to the predictor numbers in Table 4.1.

a. Annual time-scale						
Source	df	SS	MS	F-Value	Pr.(F)	$R^2$
P 15	1	1183.6	1183.6	8058.2	< 0.000001	(aajustea K)
P 16	1	9.4	93	63.9	< 0.000001	
Residual	496	72.8	0.147	05.7	(0.000001	
10010000	.,,,	/210	01117			0.9424
Variable	Coefficient	SE	t-ratio	Pr(>/t/)		(0.9421)
P. 15	-0.6030	0.0386	-15.6	0.00000		
P. 16	0.4543	0.0568	7.9	0.00000		
		b	Biennial time	-scale		
Source	df	SS	MS	F-Value	Pr(F)	$R^2$
						$(adjusted R^2)$
P. 20	1	57.82882	57.82882	2007.258	< 0.000001	
P. 21	1	3.87963	3.87963	134.663	< 0.000001	
P. 22	1	5.18835	5.18835	180.089	< 0.000001	
P. 23	1	0.45037	0.45037	15.633	0.000088	
P. 25	1	2.10140	2.10140	72.940	< 0.000001	
P. 26	1	0.59243	0.59243	20.563	0.000007	
Residuals	492	14.17445	0.02881			
Variable	Coefficient	SE	t-value	Pr(>/t/)		0.8317
P. 20	-0.4432	0.0877	-5.0533	0.00000		(8290)
P. 21	-0.2247	0.0136	-16.5077	0.00000		
P. 22	0.6328	0.0393	16.1192	0.00000		
P. 23	0.1609	0.0173	9.2915	0.00000		
P. 25	0.3890	0.0538	7.2346	0.00000		
P. 26	0.0391	0.0086	4.5347	0.00000		
			c. ENSO			_
Source	df	SS	MS	F-Value	Pr(F)	$R^2$ (adjusted $R^2$ )
P. 27	1	11.86428	11.86428	5261.259	< 0.000001	(
P. 28	1	0.33184	0.33184	147.156	< 0.000001	
P. 29	1	0.13563	0.13563	60.147	< 0.000001	
P. 30	1	0.40353	0.40353	178.945	< 0.000001	
P. 31	1	1.96307	1.96307	870.532	< 0.000001	
Residuals	493	1.11173	0.00226			0.9297
Variable	Coefficient	SE	t-value	Pr(> t )		(0.9289)
P. 27	0.4111	0.0605	6.7902	0.0000		
P. 28	-0.0521	0.0069	-7.5973	0.0000		
P. 29	-0.3924	0.0673	-5.8327	0.0000		
P. 30	0.1726	0.0138	12.5518	0.0000		
P. 31	-0.4527	0.0153	29.5048	0.0000		

1992, 1994, 1998, and 1999. In addition, the model does not perform well during the onset period, especially in 1996. However, this can be improved by including pre-monsoon months in the analysis. Inspection of the 1996 rainfall revealed increased wet conditions across much of the country early in May. This premonsoon activity continued through June. A model trained with data for June would most certainly fail to detect such signals that occasionally occur in June. Thus, training the regression model on data that include pre-monsoon months (e.g., time series for February-June) could help to forecast the onset of the season better.

The model still performs well for a 20-day (4 pentads) forecast, but the correlation between predicted and observed time series slightly decreases (r=0.67, significant at 98% probability level for a two-tailed Student's t-test). As can be seen from Fig. 4.1b, the differences between 10-day and 20-day forecasts are small. In general, the amplitudes of the forecasts diminish and the peaks and valleys shift as the forecast period increases. The forecast deteriorates for predictions further out to 6 pentads and longer (r~0.5). Thus, the model captures the low frequency variability quite accurately, and since this variability determines the overall rainfall performance, the model provides a usable prediction skill in forecasting rainfall 5-25 days in advance.



FIGURE 4.1. (a) 10-day rainfall forecast of all-Ethiopian 5-day average June-September rainfall using the wave banding technique of Webster and Hoyos (2004). (b) Comparison of 10-day and 20-day forecasts of all-Ethiopian 5-day average June-September rainfall. Pentad 1 represents the period 31 May-4 June and Pentad 25 is 27 September – 4 October.

There is stronger correspondence between observed and predicted values (Fig. 4.2a,b) when a cross validation method is employed (e.g., Wilks 1995, pp. 194), as reflected in a higher overall correlation between the two time series ( $\mathbf{r}$ =0.81, significant at 1% level). For a 20-day forecast, the correlation between observed and predicted values decreases but remains strong ( $\mathbf{r}$ =0.70, significant at 1% level). The scatter plot (Fig.4.2b) indicates a good prediction skill, except for a single outlier in 1996, which the model severely underestimated.

The forecasting skill obtained for Ethiopia is comparable to, but less than, the forecasting skill of the intraseasonal variability of the monsoon over Central India obtained by Webster and Hoyos (2004). For example, based on 1992-2003 hindcasts, the anomaly correlations for 10 and 20 days Indian rainfall predictions are +0.88 and +0.73, respectively. The high degree of predictability for the Indian monsoon is linked to the presence of well-identified effects of the monsoon intraseasonal oscillations that are manifestations of the MJO (Webster and Hoyos, 2004). As indicated in Chapter 3, for Ethiopia no connection was found between rainfall and the MJO. Despite this absence, a usable prediction skill is obtained.

Overall, the hindcast verifications show that the wave banding technique manages to forecast rainfall variability with significant skill. Based on 10 years of



FIGURE 4.2. 10-day rainfall forecast of all-Ethiopian 5-day average June-September rainfall using the wave banding technique of Webster and Hoyos (2004). (a) Time series of observed (blue line) and predicted (red line) pentad rainfall using the cross validation method. (b) Scatter plot of observed and predicted rainfall. The year labels in (a) are centered at the middle of the time series for every other year. The vertical dashed lines are drawn at the beginning of the time series every five years.

hindcasts, the wave banding scheme explained about 63% of the variance of Ethiopian summer rainfall. Although this represents a significant step in the right direction, improvements still are needed to forecast the high frequency variability with better accuracy.

## 4.3.2 Artificial Neural Network Prediction

A neural network was trained on data for 1970-89 and used as prediction model on independent data for 1990-99. The inputs are appropriately lagged pairs of predictors (Table 4.1) and rainfall for each wave band. The neural network has one hidden layer with a size twice the number of predictors, which differs for the different bands. Figure 4.3 gives the predicted and observed rainfall time series for a 10-day forecast using the NN. Although numerous trials were made, we did not succeed in increasing the correlation between predicted and observed values for the verification period. The overall correlation between observed and predicted for the 1990-99 verification period was about 0.6, which is much lower than the result obtained by the least square regression technique (Section 4.3.1). Substantial effort was made to train the neural network on the annual wave band, for which the regression technique produced near-perfect forecasts with the correlation between observed and predicted being more than +0.95. This relationship could not be reproduced by changing the neural network parameters (the size of the hidden layer, the learning rate, and the number of epochs, etc.) as discussed in Dean and Fiedler (2002). The maximum correlation

between observed and predicted values obtained from the neural network for the annual band was +0.87, which is less than the result obtained when a linear regression technique is used. Hence, in the next section, we will only consider a linear regression technique to develop prediction models for long-range forecasts.



FIGURE 4.3. A neural network 10-day rainfall forecast of all-Ethiopian 5-day average June-September rainfall using the wave banding technique of Webster and Hoyos (2004). The figure shows time series of observed (blue line) and predicted (red line) pentad rainfall for a neural network trained on 1970-89 data.

# 4.4 Long-Range Prediction

### 4.4.1 Review of Previous Studies

Hastenrath (1986) noted that climate prediction is of far greater practical importance than daily weather forecasting in a large part of the tropics where the interannual variability of rainfall is of primary concern. In Ethiopia, the provision of long-range forecasts is one of the primary tasks of NMSA. Experimental seasonal forecasting in Ethiopia started in 1987 in response to the massive catastrophic droughts in the 1980s (e.g., Gissila et al. 2004; Korecha and Barnston 2006). In the beginning, the forecasts were based on analogue and semistatistical methods. The analogue method attempts to identify regional synoptic patterns in the premonsoon seasons (e.g., atmospheric conditions in May for summer rainfall forecast) that closely match the synoptic patterns of the year for which the forecast is prepared (e.g., Nicholls and Katz 1991, p. 515). The process of finding analogue charts is labor-intensive, as historical synoptic charts are not properly archived. The analogue method suffers from subjectivity and scarcity of data, especially in earlier years when synoptic stations in the tropics that report internationally were few. Communication problems also limit available data. Due to the above problems, analogue years were selected primarily based on the state of the ENSO phenomenon.

Once the analogue years were selected, the rainfall amount and patterns in the different regions are analyzed and compared with the climatological

averages. The probabilities of above normal, near normal, and below normal rainfall are computed. This is done through frequency analysis or by ranking the regional monthly/seasonal rainfall amounts and computing their percentiles. The primary advantage of this approach is the regional detail obtained by including all observing stations in the probability analysis. However, due to the limited number of observation years, the stability of the statistical analysis is questionable. Moreover, such seasonal outlooks are simply historical analyses of probabilities of rainfall rather than predictions. Additionally, the approach only considers the overall ENSO categorization into El Niño, La Niña, and Neutral years in preparing monthly/seasonal outlooks. There are, however, clear indications that other parts of the tropical oceans, especially, the Indian Ocean, impacts summer rainfall over Ethiopia (Chapter 3). While there have been commendable successes using the above traditional approach (e.g., e.g., Nicholls and Katz 1991, p. 515), much more needs to be done to improve NMSA's forecasting capability on monthly and seasonal time-scales.

There are only a handful of published studies on long range forecasting on Ethiopia. Wood and Lovett (1974) performed arguably the earliest study on Ethiopian climate variations and forecasting. They compared the variations of 72 years (1903-74) of annual rainfall records at the Addis Ababa Geophysical Observatory with the Zurich sunspot number. Their study indicated that the 11yr solar cycle exerts strong influence on Addis Ababa rainfall, with rainfall peaks

and troughs preceding sunspot peaks and troughs by a few years. The maximum correlation between annual rainfall and sunspot numbers of +0.33 (significant at 1% level) occurs at 2 years lag. Based on this relation, the authors expected the rainfall at Addis Ababa to increase until about 1976-77 and to decline to a minimum about 5-yr later. Although we do not have records before 1951, the standardized anomalies for Addis Ababa for 1951-1999 indicate significantly reduced annual rainfall in much of the first half of the 1970s, and increased rainfall during 1977-1990 (excluding 1978 and 1984 during which rainfall anomalies were negative). Clearly, Wood and Lovett's (1974) prediction did not hold because of the low correlations. Of further interest in this study, however, is the historical distribution of Ethiopian droughts (recorded by travelers and historians) from 1540-1974 relative to sunspot minima. From their Figure 3, about 41 percent of the known Ethiopian droughts occurred 1-2 years before and about 26 percent 1-2 years after sunspot minima, indicating that about two-thirds of Ethiopian droughts (18 out of 27) tend to concentrate in the 4 years centered on sunspot minimum. However, the statistical significance of this distribution and the quality of the historical records of droughts and drought related famines in Ethiopia are unclear. We will assess the potential predictability of all-Ethiopian rainfall based on variations in sunspot numbers in the next section.

A more comprehensive empirical seasonal rainfall prediction model for Ethiopia was developed by Gissila et al. (2004). They used SSTs over the tropical oceans for March, April, and May to forecast June–September rainfall using linear regression. The authors addressed basic issues such as the implications of spatial rainfall variability and variations in the predictability of rainfall within the country. However, the study used widely scattered synoptic station data in developing the model. Although the model is a huge improvement for forecasting seasonal rainfall, it does not address intraseasonal variability within the monsoon, as it does not have a provision to forecast monthly rainfall. The prediction skill of their model also is moderate – for a one-month lead time, the correlation between observed and predicted rainfall is 0.6.

Recently, Korecha and Barnston (2006) developed a statistical seasonal forecasting model for Ethiopia using linear regression. They used March-April SSTs and their trends over the Atlantic and Pacific Oceans and model forecasts of SSTs for the Niño-3 region for the summer months to predict June-September rainfall. They found usable skill to forecast the Ethiopian rainfall anomaly within a short lead time of the summer season. The skill of their model is better than that of Gissila et al. (2004). Based on the cross validation method, they found a correlation of +0.64 between observed and predicted rainfall anomalies. The skill of the forecast, however, drops when tested on independent data (retroactive validation), the correlation between observed and predicted rainfall anomalies being +0.51. As will be shown in Section 4.4.3, the technique we employ provides higher skill and for longer lead times.

#### 4.4.2 Sunspot Numbers and Ethiopian Rainfall

With a view to assessing the predictive potential of the 11-year solar cycle, we have examined the relation between rainfall and sunspot numbers for the recent observational rainfall records for Ethiopia for 1970-99. monthly rainfall all-Ethiopian totals are computed by averaging monthly rainfall totals over 100 stations across the monsoon regions of Ethiopia for each month for January-December. Monthly sunspot numbers for the corresponding period are obtained from the NASA website at http://science.nasa.gov/ssl/pad/solar/greenwch/spot\_num.txt. The monthly averages show the number of sunspots visible on the sun with they wax and wane approximate 11-year cycle as an (http://science.nasa.gov/ssl/pad/solar/sunspots.htm).

Figure 4.4a shows the time series of monthly sunspot numbers and all-Ethiopian monthly rainfall totals for 1970-99. The correlation between the two time series is near zero (+0.04) and remains negligible for different lags. The maximum correlation obtained when rainfall leads/trails the sunspot numbers by up to 36 months is +0.13. This clearly indicates that the high frequency variability in all-Ethiopian monthly rainfall is not reflected in the sunspot number variations on monthly time-scale. However, when the monthly rainfall totals are smoothed by a 3-yr running mean, there is a modest correlation of +0.42 when each year's sunspot number is correlated with the previous year's



FIGURE 4.4. Time series of sunspot numbers and all-Ethiopian rainfall totals for 1970-99. (a) Monthly all-Ethiopian rainfall totals (red line) and sunspot numbers (blue line). (b) Same as (a) except for standardized time series. The all-Ethiopian standardized monthly rainfall in (b) is smoothed by a 3-yr running mean.

rainfall. Figure 4.4b shows standardized all-Ethiopian monthly rainfall totals and monthly sunspot numbers. The rainfall time series is smoothed by a 36-month running mean, and thus 18 months of data are lost at the ends of the rainfall time series. Inspection of the figure indicates a modest degree of correspondence between the two time series. However, both the loss of data at the end of the rainfall time series as well as the modest correlation value reduces the usability of a sunspot-based prediction model on monthly bases. In addition, even after the smoothing, there still remains strong seasonal variability that overshadows the interannual and interdecadal variability reflected in both rainfall and sunspot number time series.

The sunspot number is better related with the annual all-Ethiopian rainfall totals (Fig. 4.5). The correlation between rainfall and sunspot numbers is +0.41 at 1-year lag when rainfall precedes sunspot numbers. Although removing the seasonality increased the correlation value, the strong interannual rainfall variability appears to diminish the good correspondence between the interdecadal rainfall variability and the 11-yr solar cycle (Fig. 4.5). Overall, the quality of annual rainfall on a national scale can be inferred from variations in sunspot numbers. Thus, reduced all-Ethiopian annual rainfall is likely to lead reduced sunspot activity and vice versa.



FIGURE 4.5. Time series of standardized annual all-Ethiopian rainfall totals (red line) and sunspot numbers (blue line) for 1970-99.

### 4.4.3 SST-Based Predictions of Monthly and Seasonal Rainfall

Sea surface temperature strongly influences seasonal rainfall anomalies around the tropics and has been widely used as predictor in long-range statistical rainfall forecasts in Africa (e.g., Folland et al. 1991; Barnston et al. 1996; Gissila et al. 2004; Korecha and Barnston 2006). Many studies suggest a strong influence of Indian Ocean SST on African rainfall (Hastenrath et al. 1995; Goddard and Graham 1999, Latif et al. 1999). For Ethiopia, Gissila et al. (2004) and Korecha and Barnston (2006) have highlighted the predictability of summer rainfall using SSTs over different ocean basins. In this study, we develop physically consistent prediction model of high temporal resolution, strong skill, and long lead times using global SSTs. We use the wave banding technique of Webster and Hoyos (2004) to predict monthly rainfall totals and standardized June-September rainfall anomalies over the monsoon regions of Ethiopia. To test the usability of this approach on finer spatial scales, the predictability of rainfall anomalies is examined for a single station over the drought-prone regions of northeastern Ethiopia for the peak month (August) of the monsoon season.

#### 4.4.3.1 Monthly Rainfall Prediction through Judicious Selection of Predictors

In this section, we make use of the results of Section 3.4 in identifying regions of large-scale SST variations that strongly influence Ethiopian rainfall. Since we primarily are concerned with the monsoon season, we use monthly rainfall totals averaged over all monsoon regions of Ethiopia. However, rather than limiting the time series to the monsoon months, we took the entire January-December time series. For each of the 5 wave bands discussed in Section 3.4, 8-14 regions of large-scale SST variability that show strong association with identically wave banded rainfall have been identified. These regions include the Arabian Sea, the Mediterranean Sea, the Gulf of Guinea, the Mozambique Channel, South and East China Sea, the Philippines Sea, and many regions of the Atlantic, Pacific, and Indian oceans. Using the stepwise regression technique, only those predictors with F-ratio significant at 1% level were retained for each band. Table 4.3 lists the predictors retained in the regression model.

Predictor	Period	Region	Location
No.			
1	Seasonal	Arabian Sea	7.5°–25.0°N, 50.0°–75.0°E
2	Less than	Southern Indian Ocean	27.5°–37.5°S, 60.0°–90.0°E
3	235 days	Philippines Sea	10.0-22.5°N, 140.0°–145.0°E
4	Annual	Arabian Sea	5.0°–22.5°N, 52.5°–67.5°E
5	235days	Southern Indian Ocean	27.5°–37.5°S, 60.0°–90.0°E
6	to	South Atlantic	27.5°–37.5°S, 10.0°–40.0°W
7	1.47 yrs	North Atlantic	12.5°–25.0°N, 20.0°–50.0°W
8		South China Sea	2.5°–22.5°N, 100.0°–125.0°E
9		Philippines Sea	20.0°-32.5°N, 120.0°-140.0°E
10	Biennial	Southeastern Indian Ocean	37.5°–42.5°S, 85.0°–100.0°E
11	1.47	Western equatorial Indian Ocean	5.0°S–5.0°N, 42.5°–52.5°E
12	to	Northern tropical Atlantic	35.0°–45.0°N, 35.0°–50.0°W
13	2.57 yrs	Eastern equatorial Pacific	0°-5.0°S,80.0-102.5°W
14	-	Southwestern topical Pacific	10.0°–17.5°S, 155.0°–170.0°W
15		East China Sea	25.0°-35.0°N, 122.5°-132.5°E
16	ENSO	Central Indian Ocean	0°–7.5°S, 75.0°–80.0°E
17	2.57	Southwestern Indian Ocean	40.0°-45.0°S, 55.0°-65.0°E
18	to	Southern Indian Ocean	52.5°–57.5°S, 82.5°–90.0°E
19	4.47 yrs	Western tropical Pacific	5.0°-10.0°S, 122.5°-137.5°E
20	•	Northern Pacific	27.5°-32.5°N, 170.0°-190.0°E
21	Low-	Western Indian Ocean	2.5°–7.5°N, 50.0°–57.5°E
22	frequency	Southern Indian Ocean	5.0°-15.0°S, 70.0°-75.0°E
23	> 4.47	Western Mediterranean Sea	32.5°-40.0°N, 2.5°-12.5°E
24	yrs	Northern Pacific	27.5°–32.5°N, 155.0°–
	-		167.5°W

Table 4.3. Predictors chosen by stepwise regression model with the F-ratio significant at the 1% level.

Inspection of the predictors retained by the stepwise regression indicates that large-scale SST variability over many parts of the Indian Ocean is critically important in explaining the variability of Ethiopian rainfall. On the seasonal to annual time-scales, the Arabian Sea exerts strong influence. For the biennial and ENSO modes, SST variability over the equatorial and tropical Pacific and the Indian Ocean are important. In agreement with our previous findings, the Atlantic Ocean possesses strong predictive signals for Ethiopian rainfall. These findings are consistent with results of Gissila et al. (2004).

Figure 4.6 shows predicted and observed monthly rainfall values for a 3month lead forecast for retroactive (Fig. 4.6a) and cross validation (Fig. 4.6b) approaches. Overall, the model performs very well for both verification methods. The annual cycle is very well represented; the valleys and peaks of the forecasts match the observed with a high degree of accuracy. On the other hand, inspection of the figure indicates that the model shows weakness in predicting spring rainfall. However, since the monthly averages were computed over the entire monsoon region, including the regions that do not normally receive spring rains, the predictand itself does not consistently exhibit the short rains variability. Hence, the model weakness during the spring season is due primarily to the problem of the averaging.

The correlations between predicted and observed rainfall for the retroactive and cross-validation methods are 0.897 and 0.906, respectively. The linear regression model developed through the wave banding technique explained more than 80% of the variance of Ethiopian annual rainfall cycle. The fact that the model explains such large proportion of the total rainfall variability when tested on independent data makes the model very dependable, practical, and usable.



FIGURE 4.6. Three-month lead time forecasts of all-Ethiopian monthly total rainfall using the wave banding technique of Webster and Hoyos (2004). (a) Time series of observed (blue line) and predicted (red line) monthly rainfall. Predicted values are obtained by applying the model developed for 1970-89 on the independent data for 1990-99. (b) Same as (a) except for cross validation method in which the model is developed using data for all years except for the one year on which the model is validated. The year labels in (b) are centered at the middle of each year's time series.

Although the time scales are different, the skill of the long range forecasts is higher than the results obtained for medium range (5-25 days) forecasts for both Ethiopia (Section 4.3), and India (Webster and Hoyos 2004). Our model is superior to the model developed by Gissila et al. (2004) and Korecha and Barnston (2006) for June-September rainfall forecasts for Ethiopia. As discussed in Section 4.4.1, for a 3-4 month lead time the maximum correlation between observed and predicted time series that Gissila et al. (2004) and Korecha and Barnston (2006) obtained were 0.6 and 0.64, respectively.

Additional indication of the model superiority is its ability to forecast monthly rainfall at very long lead times. Figure 4.7 shows the correlation between predicted and observed rainfall for different lead times using the retroactive and cross validation methods. The cross validation method shows higher skill than the retroactive method because of the larger number of years used to train the model and due also to the presence of serial correlation in the monthly data. To examine whether the serial correlation affects the statistical significance, the number of independent data is determined using the relation (e.g., Wilks 1995, pp. 315-316)

$$N_{e} = N \left[ 1 + \frac{2}{N} \sum_{k=1}^{N} (N-k)\rho(k) \right]^{-1}$$
(4.5)

where,  $N_e$  is the effective degrees of freedom, N is the length of the original time series, and  $\rho(k)$  is the autocorrelation of the time series at lag k. After



FIGURE 4.7. Correlation between observed and predicted monthly all-Ethiopian rainfall for different lead times for cross validation (red line) and retroactive validation (blue line). For the cross validation method, the model is developed using data for all years except the one year on which the model is validated. For the retroactive verification method, the model is developed for 1970-89 and verified on the independent data for 1990-99.

taking into account the reduction in the independent degrees of freedom due to the serial correlation, the correlation between observed and predicted rainfall remains significant at 1% level.

## 4.4.3.2 Prediction of Monthly Rainfall Totals Using EOF Analysis

Eigentechniques have been used as pure data reduction tool to aid in forecasting (e.g., Richman 1986; Barnston et al. 1996). EOF analyses reduce a

large number of original variables to fewer essential variables that contain much of the large-scale variability (e.g., Folland et al. 1991; Barnston et al. 1996). As an alternative to the subjective selection of predictors (based on correlation analysis assessment) as done in previous sections, here the SVD analysis of wave banded global SST is applied to obtain the PC time coefficients of the dominant modes of SST variability for each of the 5 wave bands discussed in Section 3.4 and Section 4.4.3.1. These time series then are fed into a stepwise regression to develop a parsimonious prediction model. The temporal orthogonality of the PCs makes them suitable to be used for regression (Richman 1986). Because the main purpose of the analyses is data reduction, rotation of the EOFs is unnecessary (Richman 1986; Barnston et al. 1996).

The SVD analysis was performed on 1° x 1° SST filtered anomalies covering the region from 60°S to 60°N. For each wave band, the first 10 PCs were retained. Various tests can be made to determine the number of PCs to retain (e.g., scree, LEV, Preisendorfer and Barnett tests; e.g., Richman 1986). A plot of the eigenvalues against the mode number suggests retaining 15-20 PCs for the first two wave bands (period less than 1.47 years) and about 10 to 15 PCs for the remaining 3 modes (not shown). Here, 10 PCs were retained for each mode.

For the wave band with period less than 235 days, the first 10 unrotated PCs account for only 17% of the total SST variability. For the annual and biennial
modes, the first 10 PCs explain 60 and 67% of the total SST variability for each mode, respectively. For the remaining two larger period wave bands, the unrotated 10 PCs explain 83-89% of the total SST variability. After stepwise regression, 4 PCs were retained for each of the modes with periods less than 1.47 years, and 7-9 PCs were retained for the remaining bands. A summary of the model performance is shown in Table 4.4. For wave band I (period < 235 days), the model performance is good and accounts for 46% of rainfall variability in that mode. The models perform very well for the other four modes. In particular, for the annual, ENSO, and low-frequency modes, the models explain more than 96% of the variability of the respective modes. This reflects an exceptional model performance.

developed for 1970-89.							
	Wave band						
	Ι	II	III	IV	V		
	< 235	235 days-	1 47-2 57	2 57-4 47	$> 4.47 \mathrm{vrs}$		

-

Table 4.4. Summary of stepwise regression results. The R-squared is for the models developed for 1970-89.

	1 < 235 days	11 235 days- 1.47 yrs	111 1.47-2.57 yrs	1V 2.57-4.47 yrs	V > 4.47yrs
Number of PC predictors	4	4	7	9	9
R-Squared	0.4645	0.9722	0.6786	0.9777	0.9684
P-value of	< 0.00001	< 0.00001	< 0.00001	< 0.00001	< 0.00001
model F-statistic					

Figure 4.8 shows the spatial patterns of the primary EOF modes that have the lowest standard error and highest F-ratio in the model and the strongest correlation with rainfall for each wave band. For the first wave band, EOF1 has the highest F-ratio, and exhibits the highest amplitude over the Arabian Sea (Fig. 4.8a). SST variation over the Arabian Sea was also one of the primary predictors used for the model developed in Section 4.4.3.1 (Table 4.3). Thus, consistent with our earlier discussion in Section 3.4, the seasonal rainfall variability is prominently affected by SST variation over the Arabian Sea.

On the annual time-scale, both EOF1 and EOF2 show substantial F-values and small standard errors. EOF1 exhibits strong amplitudes over western parts of the northern hemisphere oceans (Fig. 4.8b). It thus appears that SST variations over the subtropical/midlatitude oceans exert strong influence on Ethiopia's annual rainfall cycle. For the biennial mode, EOF7 shows the highest F-value in the model, but interpretation is difficult owing to the complex patterns in the amplitudes (Fig. 4.8c). However, at this time-scale, rainfall variations appear to be associated with SST variations over the southern Indian Ocean, southwestern Atlantic, and northern Pacific. For the ENSO and the low-frequency modes, EOF1 SST variations in the equatorial Pacific exhibit strong amplitudes (Figs. 4.8d, e). The classical ENSO pattern with extensive area of positive PC loadings corresponding to a positive SST anomaly over the eastern equatorial Pacific in Fig. 4.8d is noteworthy. Significant amplitudes of same polarity as in the Pacific



FIGURE 4.8. Spatial patterns of EOFs for wave band filtered global SST. (a) EOF1 for SST filtered for periods less than 235 days. (b) EOF1 for SST filtered from 235 days-1.47 years. (c) EOF7 for SST filtered from 1.47-2.57 years. (d) EOF1 for SST filtered from 2.57-4.47 years. (e) EOF1 for SST filtered for periods greater than 4.47 years.

are also evident over the Indian Ocean. For the low-frequency mode, SST variations over the Indian Ocean and northeast Pacific affect rainfall over Ethiopia.

The overall performance of the model is tested using cross-validation and retroactive validation methods, as discussed in Section 4.3.1. Figure 4.9 shows a 3-month lead time forecast. For the retroactive validation method (Fig. 4.9a), the performance of the model is essentially the same as that in Section 4.4.3.1. The correlation between observed and predicted values for the retroactive verification method is +0.896. Again, the major peaks and valley are reproduced, although their absolute values are underestimated. Noticeable departures from the observed patterns are evident, especially in 1992 and 1998. For the cross validation method, the skill slightly increases with a correlation value of 0.916 (Fig. 4.9b). Other than underestimating the peaks, the model performs exceptionally well.

### 4.4.3.3 Predicting Standardized Seasonal Rainfall Anomalies

Another seasonal rainfall prediction model was developed for the monsoon region of Ethiopia, this time using standardized all-Ethiopian June-September rainfall values. The standardized index was constructed using 100 raingauge stations for 1970-99. Standardized anomalies were obtained by dividing the seasonal rainfall anomalies by the standard deviation for each year and station, and then averaging across stations for individual years. Wavelet analysis was



then performed on this index time series (30 data points). The global wavelet spectrum is shown in Fig. 4.10. The dominant power is concentrated on the biennial (1-3 years), ENSO (3-9 years), decadal (9-19 years), and multidecadal

(>19 years) time-scales. The variance at the multidecadal time-scale, however, is corrupted by padding zeros to the end of the time series.



FIGURE 4.10. Global wavelet spectra of standardized June-September all-Ethiopian rainfall index for 1970-99. The amplitude is normalized by the total variance for the entire period at each frequency.

We used global 1° x 1° SSTs for March as predictors. This gives sufficient lead time for the prediction of June-September rainfall anomalies before the onset of the season. Both the seasonal standardized rainfall index and global SSTs for March were identically bandpass filtered on the above four time-scales. As in Section 4.4.3.2, SVD analysis was performed on filtered SST anomalies covering 60°S to 60°N. A scree test suggests retaining 15-18 PCs for the first two wave bands, and 3-5 PCs for the decadal and multidecadal time-scales. The retained PCs explain more than 96% of the total variance for each wave band.

Using a stepwise least squares linear regression technique, the best predictors with F-values significant at the 1% level were selected for each wave band. Table 4.5 gives a summary of the model performance and the number of PCs retained in the final regression models. For each mode, the model explains more than 98% of the total variance. However, a relatively large number of PCs had to be retained for the biennial and ENSO modes in order for the model to capture a large percentage of the total variance.

Table 4.5. Summary of stepwise regression results. For cross validation, the R-squared value is the average for 30 regression models that are constructed for all years excluding each of the 30 years in turn. The R-squared for the retroactive validation is for the model developed for 1970-89.

		Wave band			
		Ι	II	III	IV
		1-3 yrs	3-9 yrs	9-19 yrs	>19 yrs
Number of PC predictors		9	12	6	3
R-Squared	Cross validation	0.981	0.973	0.999	0.999
	Retroactive	0.991	0.997	0.999	0.999

Figure 4.11 shows the spatial patterns of the primary EOF modes for biennial, ENSO, and decadal modes. For the biennial mode, EOF1 has the largest F value. This mode exhibits the highest positive amplitudes over the southern Indian Ocean, northern and southern subtropical Pacific, and negative loadings over northern Arabian Sea, northeastern and southeastern Pacific (Fig. 4.11a). Thus, SSTs in these regions exert the strongest influence on the forecast skill. EOF1 for the ENSO mode exhibits large positive amplitudes over the Indian Ocean, the equatorial Pacific and negative amplitudes over the subtropical and western Pacific (Fig. 4.11b). The EOF patterns over the equatorial Pacific clearly indicate an ENSO signature, but SSTs over the Indian Ocean are equally important in explaining rainfall variations over Ethiopia at this time-scale. In fact, the highest contribution to the forecast comes from EOF6, which shows strong amplitudes over eastern Indian Ocean, southern Atlantic, and the equatorial Pacific (not shown). On the decadal time-scale (Fig. 4.11c), SSTs over the Indian, Pacific, and Atlantic oceans exert strong influence on Ethiopian rainfall, with the strongest EOF amplitudes occurring over the northern subtropical Pacific and Atlantic oceans.

To skill of the model again is assessed using retroactive and cross validation techniques. For the retroactive approach (Fig. 4.12a), the correlation between observed and predicted standardized rainfall anomalies is 0.88 (statistically significant at 99.9% level). The model accurately identifies the sign of the



FIGURE 4.11. Spatial patterns of the first EOFs for global March SSTs wave band filtered for periods of (a) 1-3 years, (b) 3-9 years, and (c) 9-19 years.

standardized anomalies for all years except for 1992, for which the observed anomaly is less than 0.20. The performance of the model is exceptional for the cross validation method in which each of the 30 years is held out in turn and the



FIGURE 4.12. Predictions of all-Ethiopian standardized June-September rainfall anomalies using the wave banding technique of Webster and Hoyos (2004). (**a**) Time series of observed (red) and predicted (green) anomalies. Predicted values are obtained by applying the model developed for 1970-89 to the independent data for 1990-99. (**b**) Same as (**a**) except for cross validation method in which the model is developed using data for all years except the one year for which the model is validated. EOFs of March SSTs were used as predictors.

model is developed using the remaining 29 years (Fig. 4.12b). The correlation between observed and predicted is 0.98. Again, the model accurately identified the sign of the anomalies for all years except for 1976-77, during which the observed anomalies were near zero. The skills obtained through cross validation method by Gissila et al. (2004) and Korecha and Barnston (2006) in forecasting seasonal rainfall anomalies for Ethiopia are much lower than what our study finds on independent data (1990-99).

In general, the wave banding technique has provided a dependable prediction model for Ethiopia in forecasting seasonal rainfall anomalies with accuracy that has never been achieved before. In addition to the exceptionally strong skill computed through the cross validation hindcasts, the prediction model explains about 78% of the total seasonal rainfall variability when applied on independent data (1990-99). Our success to forecast both monthly total rainfall and seasonal anomalies with such accuracy would play a key role in combating the damaging effects of the recurring droughts in Ethiopia. In the next section, we examine the applicability and utility of the wave banding technique for forecasting rainfall anomalies at the peak of Kiremt at a specific representative drought-prone location.

#### 4.4.3.4 Localized Prediction

To examine the value of the wave banding technique in predicting rainfall on finer spatial and temporal scales, the technique was applied to predict August rainfall anomalies for a synoptic station in Combolcha (Fig. 4.13). The location lies at the center of one of the most drought-prone regions of northeastern Ethiopia. The standardized August rainfall anomalies were computed using station mean and standard deviation for 1970-99 time series, during which there was no missing observations. The global wavelet spectrum for Combolcha (Fig. 4.13) shows that the dominant variability occurs at the ENSO time-scale (3.6-7.7 years) with a peak at 5.8 years. The second most dominant power comes from the decadal variability (7.7-20 years) with a peak at 10 years, followed by the biennial variability in the 1-3.5 years band with a peak at 2.4 years. Unlike the case for the all-Ethiopian standardized June-September anomalies, the power at the multi-decadal time-scale (> 20 years; peak at 30 years) is very small, accounting for only 1.2% of the total power at its peak.



FIGURE 4.13. Same as Fig. 4.10 except for Combolcha for August.

To predict August rainfall anomalies, we used global SSTs for April as predictor, allowing a 3-month lead time for prediction. Both SSTs and rainfall were wave band filtered for the above four dominant modes (biennial, ENSO, decadal, and multidecadal). The SSTs then were orthogonalized using the SVD techniques. A plot of the singular values suggests retaining 18, 15, 8, and 2 PCs for the biennial, ENSO, decadal, and multidecadal modes, respectively. These PCs explain more than 99% of the total variance of the filtered SSTs for each mode.

For each mode, these predictors were fed into a stepwise least squares linear regression model and the best predictors with F-values significant at 98% level were selected. Table 4.6 gives the number of PC predictors used in the final regression models and summarizes the model performance. For the biennial mode (Wave band I), the variance explained by the model is relatively low due to the small number of predictors retained. While increasing the number of predictors gave very high R-squared for the cross-validation technique, the same predictors fail to capture the variability when applied on independent data (i.e., on data for the same station but for 1990-99), rendering the regression coefficients statistically not significant. Hence, we chose to limit the number of PCs used for the biennial mode to 4. For the ENSO mode, all the predictors used give very high F-ratios and stable coefficients for both approaches. The models for the

other two modes capture rainfall variability with a high degree of accuracy with a relatively small number of predictors.

		Wave band				
		Ι	II	III	IV	
		1-3.5 yrs	3.5-7.7 yrs	7.7-20 yrs	>20 yrs	
Number of PC predictors		4	8	5	2	
R-Squared	Cross-validation	0.657	0.998	0.989	0.999	
	Retroactive	0.761	0.993	0.997	1.000	

Table 4.6. Same as Table 4.5 except for Combolcha for August.

The overall excellent performance of the scheme is demonstrated in Fig. 4.14. The correlations between observed and predicted standardized anomalies for the retroactive and cross-validation techniques are 0.89 and 0.84, respectively, which are quite high for such unsmoothed station data. Moreover, the model correctly identifies the signs of the standardized anomalies except in few cases (1993 for retroactive; 1971, 1988, and 1993 for the cross-validation). However, except for 1993, the observed anomalies in 1971 and 1988 are very small. The few cases in which the model failed to capture the correct signs of the anomalies can be utilized to gauge the usability of the forecasts by constructing a simple climatological probability of success/failure. The most important and societally relevant quality of this model is its ability to forecast the most extreme years (e.g., 1984).



FIGURE 4.14. Same as Fig. 4.12 except for Combolcha for August.

Comparison of Figs. 4.12 and 4.14 highlights the importance of forecasts with high spatial and temporal resolution. While the observed (and also predicted) anomalies for Combolcha largely are reflected in the all-Ethiopian standardized June-Sept anomalies (e.g., wetter conditions in 1975 and 1996, and drier conditions in 1972 and 1984), the extreme 1987 seasonal deficit in all-Ethiopian rainfall does not appear in the August 1987 rainfall anomalies for Combolcha, which actually received excess rainfall in that month. However, this station experienced deficient rainfall for part of the 1987 season. Inspections of the monthly and seasonal rainfall anomalies for Combolcha show that a large rainfall deficit in July contributed to an overall dry condition of June-September 1987. Thus, in addition to an overall nationwide seasonal forecast, the ability to forecast monthly rainfall distribution for a specific site could help to effectively utilize resources and manage droughts.

# 4.5 Summary

The statistical prediction models developed in this study have shown excellent predictive skill, especially on monthly and longer time-scales. Although the intraseasonal (less than a month) forecast skill is not as good as the monthly and seasonal empirical prediction skill, the intraseasonal empirical model has provided very good forecasts that compare well with observations for Ethiopia. The performance of the intraseasonal model for Ethiopia also compares well with the statistical forecast skill found by Webster and Hoyos (2004) for Indian monsoon rainfall prediction on 10-30-day time range, especially considering the absence of any MJO-rainfall link for Ethiopia. For monthly to seasonal predictions, our models perform exceptionally well and are superior to previous linear regression models developed for Ethiopia (Gissila et al. 2004; Korecha and Barnston 2006). Note that we could not compare the quality of our monthly to seasonal forecasts with the results of Webster and Hoyos (2004) since their predictions were for shorter time-scales (10-30 days).

In general, the banded-wavelet scheme has great potential for predicting rainfall at different time-scales. The results of this part of the study make it clear that Ethiopian rainfall is highly predictable on longer time-scales (> 30 days). Although further improvements to the long-range forecast model possibly could be achieved by including atmospheric predictors, especially where SST predictors alone perform only moderately for the shorter time-scale modes, the results demonstrate the enormous predictive value of global SST for long-range rainfall prediction in the tropics. One of the weaknesses of the wave banding technique is the reduction of the amplitudes of the forecasts. However, a study of the model climatology can help to rectify the problem by adding a known bias to the forecast. Likewise, the climatology of prediction quality expressed as probability of success/failure can be incorporated into the forecasts to enhance users' confidence in the prediction.

However, the usability of such skillful predictions largely depends on whether the forecasts are target oriented. Seasonal forecasts should be based on a clear understanding of societal needs (e.g., Broad and Agrawala 2000). Lamb (1981) and Sonka et al. (1982) suggest that the practical applicability of climate forecasts requires (1) identifying human activities most severely affected by climate fluctuations in geographic regions, (2) determining the most affected regional economic sectors that possess the flexibility to adjust and benefit substantially from climate forecasts, and (3) developing skillful climate prediction schemes geared towards reducing the stresses climate variability imposes on society in such regions. These requirements entail testing, validation, and adaptation of research findings for practical application under local conditions, as well as an intensive and continuous interaction among climate scientists, decision makers, and climate information users (e.g., Broad and Agrawala 2000; Tarhule and Lamb 2003). The apparent strong capability of the wave banding technique allows us to tailor forecasts to achieve a desired goal for a specific targeted economic sector as suggested by Lamb (1981).

Agriculture is one of the most severely affected economic sectors in Ethiopia. Through active cooperation with the social and agricultural scientists, economists, and other planners, regions of significant agricultural interests can be identified and the specific agricultural activities and cropping patterns can be assessed. In addition, the necessary lead time and the required precision of the forecasts can be known. With this knowledge, target oriented predictions can be designed. Thus, seasonal forecasts of total rainfall and anomalies can be prepared to assess the overall quality of a season, which could help, for example, in deciding the types of crops or the variety of seeds to plant. A skillful monthly forecast can then be designed to predict rainfall anomalies/total amounts. Such forecasts could help in deciding the use of agricultural inputs (e.g., pesticides or fertilizers) thereby avoiding the waste of resources (Ethiopian farmers get such agricultural inputs in advance of the main rainy season on government loan, but struggle to pay their loan in full even in a good harvest year). The forecasts can also be of potential use during harvesting. A skillful prediction scheme can also be designed for water management purposes at a specific dam. Hydrological forecasts are important for dam safety as well as for efficient utilization of available water for energy production. Supported by a knowledge of the requirements of the user community and decision makers, we believe that this study can make a difference in reducing the adverse socioeconomic impacts of climate variability in Ethiopia.

# CHAPTER 5: APLICATION OF REGIONAL CLIMATE MODEL TO THE HORN OF AFRICA

# 5.1 Overview

# 5.1.1 Motivation

Regional Climate Models (RCMs) are widely utilized to investigate the basic state of regional climates and the physical mechanisms underlying regional climate anomalies. The National Center for Atmospheric Research (NCAR) REGional Climate Model (RegCM) has been extensively utilized for midlatitude regions (e.g., Giorgi 1991; Giorgi et al. 1993c; Giorgi and Marinucci 1996; Giorgi and Shields 1999; Small et al. 1999). However, its application in Africa has been relatively limited to East Africa (e.g., Sun et al. 1999a) and West Africa (e.g., Afiesimama et al. 2006). Prior to applying regional models for climate variability studies, the accuracy of the models in reproducing the observed climates should be assessed (e.g., Sun et al. 1999a; Lee and Suh 2000; Afiesimama et al. 2006) and their performance evaluated to establish more fully their strengths and weaknesses (Small et al. 1999).

The primary goal of this chapter is the evaluation and validation of The Abdus Salam International Center for Theoretical Physics (ICTP) version 3 RCM (RegCM3) in simulating the climate over the monsoon regions of the Horn of Africa, for which no previous modeling has been conducted. This validation

exercise is a lead in to Chapter 6, which uses the model to investigate the effects of SST variations across several ocean basins in the Atlantic and the Indian Ocean and the impacts of local vegetation coverage on monsoonal rainfall over the Horn of Africa. Because rainfall is the most important climate element for agriculture and water resources over much of the Horn of Africa, emphasis is placed on evaluating the performance of the model in producing observed rainfall amounts, distribution, and interannual variability.

# 5.1.2 The ICTP Regional Climate Model

RegCM3 is the latest version in a series of RCMs that evolved from the NCAR-Pennsylvania State University (PSU) Mesoscale Model version 4 (MM4). In the development of the earliest RCM version (Dickinson et al. 1989; Giorgi and Bates 1989), several MM4 physics parameterizations were modified to adapt it to longer-term climate simulations. In particular, the radiative transfer scheme of Kiehl et al. (1987) and the Biosphere Atmosphere Transfer Scheme (BATS; Dickinson et al. 1986) were added and existing planetary boundary layer (PBL) and convective precipitation schemes modified (Giorgi et al. 1993a; Pal et al. 2005). The earlier versions of the model have been used for a wide variety of applications including paleoclimate, climate change, aerosol climatic effects, water resources, land cover change, biosphere-atmosphere and ocean-atmosphere interactions, and seasonal predictions (Reviewed in Pal et al. 2005).

The third generation RegCM integrates almost two decades of improvements made in earlier versions in the representation of precipitation physics, surface physics, atmospheric chemistry and aerosols, PBL parameterizations, radiative transfer, and BATS (Pal et al. 2005). The dynamical core of RegCM3 is based on the NCAR/PSU Mesoscale Model version 5 (MM5; Grell et al. 1994), and is a compressible, primitive equation, sigma vertical coordinate, grid point limitedarea model with hydrostatic balance (Giorgi and Marinucci 1996; Giorgi and Shields 1999, Pal et al. 2005).

In RegCM3, a non-local formulation of Holstang et al. (1990) is used to represent PBL processes. In this formulation, the vertical eddy flux within the PBL is given by an eddy diffusion term and a "countergradient" term that describes the nonlocal vertical transport due to dry convection (Georgi and Marinucci 1996; Pal et al. 2005). Details of its implementation in RegCM3 are described in Giorgi et al. (1993c). The radiative transfer scheme is from the Community Climate Model version 3 (Kiehl et al. 1996). This scheme treats the radiative effects of water vapor, ozone, carbon dioxide, oxygen, atmospheric aerosols, cloud water, cloud ice, and some greenhouse gasses such as NO<sub>2</sub>, CH<sub>4</sub> and CFCs using the delta-Eddington approximation over 18 discrete spectral intervals (e.g., Giorgi and Marinucci 1996; Pal et al. 2005); http://www.ictp.trieste.it/~pubregcm/RegCM3/regcm.pdf).

BATS describes the surface processes and represents the role of vegetation and soil moisture in modifying the surface-atmosphere exchanges of momentum, energy, and water vapor (Giorgi and Marunucci 1996). BATS contains a vegetation layer with 19 land cover types, a snow layer, and a three-layer soil water model (a 10 cm surface soil layer, a 1 to 2 m root zone, and a 3 m deep soil layer). Prognostic equations are solved for soil layer temperature, water content and, in the presence of vegetation, canopy air and foliage temperature (Giorgi and Marunucci 1996; Pal et al. 2005). Recent additional modifications in BATS dealing with subgrid variability of topography and land cover showed marked improvement in the representation of the surface hydrological cycle in RegCM3 (Pal et al. 2005).

Large-scale (resolvable) precipitation is represented via the SUB-grid Explicit moisture scheme (SUBEX; Pal et al. 2000). There are three schemes for handling convective precipitation in RegCM3 (Pal et al. 2005). As the evaluation of model precipitation is at the core of this study, the details of the precipitation schemes will be presented in Section 5.3.

# 5.2 Regional Climate Model Technical Issues

Giorgi and Mearns (1999), Giorgi et al. (2001), and others discuss many issues related to the functioning, potentials, and limitations of the "nested" regional climate modeling technique that a growing number of RCMs users need to consider. This nesting involves a one way nesting in which the circulations produced by the nested RCM do not feed back into the global model. Giorgi and Mearns (1999) noted that although regional models can be run with two way interacting nested subdomains, two way interacting experiments between global and regional models have not been attempted. The primary technical issues summarized below are spin-up, lateral boundary conditions, domain size and resolution, and model physics.

# (a) Spin-up

As the climatology of a RCM essentially involves dynamical equilibrium between large-scale external forcing and internal model forcing (e.g., forcing from topography and model physics), a significant amount of time may be required for the lateral boundary information to permeate the model domain before dynamic equilibrium is reached. This atmospheric spin-up time depends on domain size and circulation features and typically is a few days in length (Seth and Giorgi 1998; Giorgi and Mearns 1999), but can be as long as a month (e.g., Sun et al. 1999a). On the other hand, the equilibrium time for simulations with soil moisture and soil temperature initializations can be quite long and depends on the mean climate and soil depth (Qian et al. 2003). For example, to attain dynamic equilibrium, it may require a few seasons for the rooting zone (about 1 m depth) and years for the deep soils (Christensen, 1999). Generally, simulation outputs for the duration of the spin-up are discarded for model output analysis.

#### (b) Lateral Boundary Conditions

The lateral boundary condition (LBC) issue relates to the frequency, extent, and manner in which the external large-scale forcing affects the regional model. If the lateral boundary conditions are applied over a large buffer zone, internal model process may not evolve sufficiently to capture the regional-scale characteristics. On the other hand, abrupt changes at lateral boundaries (e.g., severe resolution mismatch between RCM and large-scale forcing) produce noise that contaminates model solutions.

Giorgi et al. (1993) noted that a sharp transition at the lateral boundary generates noise when model solutions are linearly relaxed toward the large scale driving fields in a narrow buffer zone, and showed that the noise is substantially reduced by using exponentially varying weighting functions over a broader buffer zone that is wider in the upper troposphere than the middle and lower troposphere. The frequency at which the lateral boundary conditions are applied depends on the season. During summer, when strong differential heating associated with the diurnal cycle may cause overturning of mesoscale circulations over land, the forcing needs to include approximate representation of the diurnal cycle. Giorgi et al. (1993) recommended that the interval of LBC update be at least 6 hours.

## (c) Domain and Resolution

The size and location of the domain and model resolution can significantly affect model solutions. The choice of domain and resolution is determined by a compromise between physical and computational considerations. Seth and Giorgi (1998) suggested that domains much larger than the area of interest may be needed for sensitivity studies, but noted that applying the lateral boundary forcing on a small domain may force the regional model to capture observed precipitation better.

While there is no universally applicable "rule of thumb", Giorgi and Mearns (1999) recommend that the domain be large enough to allow full development of internal model dynamics and include relevant regional forcing while requiring the optimal computational resources. In addition, locating boundaries over areas with significant topography may lead to inconsistencies and noise generation (e.g., Hong and Juang, 1998). The model resolution also must be fine enough to resolve adequately the scales and effects of the local forcing and must be consistent with the physical and dynamical parameterization scales in the model. At the same time, to avoid the generation of spurious circulations arising from

abrupt changes near the lateral boundaries, it should not be too small compared to the resolution of the driving large-scale circulation (Giorgi and Mearns 1999).

#### (d) Model Physics

RCM physics issues revolve around the adequacy of the representation of physical processes relevant to climate applications and its compatibility with the GCM physics that produce the large-scale driving conditions (Giorgi and Mearns 1999; Giorgi and Shields 1999). The physics adequacy issue is addressed satisfactorily through capitalizing on the scientific advances made in RCMs over the years (Giorgi and Mearns 1999). With regards to GCM compatibility, Giorgi and Mearns (1999) noted that RCM model physics configurations are either (a) derived from a pre-existing and well tested limited area model that is suitably customized for climate applications (e.g., the NCAR Regional Climate Model, RegCM; Georgi et al. 1993b), or (b) the full physics of a GCM is implemented within a regional dynamical framework (e.g., the United Kingdom Meteorological Office unified model; Jones et al. 1995). The disadvantage in for (a) is that different model physics may result in inconsistencies near the boundary or spurious circulations may develop in the interior of the domain, while the major disadvantage of (b) is that model physics developed for a GCM may not be adequate for the high resolutions used in nested regional models (Giorgi and Mearns 1999). It has been noted that multiyear RCM experiments driven by analyses of observations (e.g., reanalysis data) show better performance than GCM driven simulations (Giorgi et al. 1993b; Small et al. 1999; Qian et al. 2003). Thus, both approaches can lead to good quality simulations when driven by quality lateral boundary conditions (Giorgi and Mearns 1999; Small et al. 1999).

In customizing the RegCM3 for climate studies over the Horn of Africa, the above major issues were taken into consideration. In particular, we have applied the recommendations and utilized the results of past studies (e.g., Giorgi et al. 1993; Giorgi and Mearns 1999; Sun et al. 1999a) on the selection of the model physical characteristics—model domain size, location, resolution, frequency of LBC update, size of buffer zone, and spin up time. Details are presented in Section 5.4. One of the most important components of the model physics is the formulation of precipitation processes. Because of its importance, the theoretical details of the precipitation schemes available for use in RegCM3 now are discussed.

# 5.3 Precipitation Schemes in RegCM3

The inadequate treatment of cumulus convection is one of the major sources of errors in climate models (Pal et al. 2005), especially during summer when convective processes are important (Giorgi and Marinucci 1996), and the influence of subgrid scale processes on precipitation is greater (Small et al. 1999). In addition, Giorgi and Bates (1989) and Giorgi et al. (1993a) showed that the biases of simulated precipitation from observed tend to be large in mountainous regions. In fact, in the early stages of regional climate modeling, all convective schemes produced low simulated precipitation skill during summer, with excessive amounts especially over mountainous regions (Giorgi 1991). For example, the Kuo-type parameterization (Anthes et al. 1977), in which precipitation is initiated when moist convergence in a column exceeds a certain threshold and the column is convectively unstable, produced excessive rainfall with the total bias exceeding 176% over western United States (Giorgi 1991).

The performance of a RCM thus depends on the particular convective scheme utilized. Therefore, it is important to examine the performance of a regional model for the different available cumulus parameterization schemes before applying it to simulate the past, current, and future climate of a tropical mountainous region like the Horn of Africa.

As noted above, RegCM3 precipitation is produced in two different forms: resolvable (large-scale) and convective (subgrid). The resolvable precipitation is associated with large-scale systems, and is represented via the SUB-grid Explicit moisture scheme (SUBEX; Pal et al. 2000). Convective precipitation typically occurs in the tropics in summer at scale finer than 1-km (Pal et al. 2005). Three physics options were available to treat convective precipitation: (1) the modified Anthes-Kuo scheme (Anthes, 1977, Giorgi 1991; Giorgi et al. 1993b); (2) the Grell

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scheme (Grell 1993); and (3) the Massachusetts Institute of Technology (MIT) scheme (Emanuel 1991; Emanuel and Živković-Rothman 1999). These resolvable and convective precipitation schemes now are described.

#### 5.3.1 Resolvable-Scale Precipitation Scheme

Resolvable precipitation can be represented by an implicit or explicit scheme. In the implicit scheme, supersaturated water immediately precipitates when relative humidity of 100% is exceeded at a grid point (Giorgi and Marunucci 1996; Sin et al. 1999a). The explicit scheme is used in numerical weather predictions (NWP) and consists of prognostic equations for cloud water and rain water mixing ratio that represent processes including advection by large-scale wind, diffusion by subgrid-scale motions, condensation/evaporation of cloud water and rain water, aggregation of cloud water by rainwater, and gravitational settling of rainwater (Giorgi 1991; Giorgi and Marunucci 1996). Instead, the full explicit scheme is computationally too expensive to be used in climate models because it adds about 30%-50% of computation time to RegCM (Giorgi and Marunucci 1996). The computationally inexpensive scheme, SUBEX, is utilized. This scheme accounts for the subgrid-scale variability of clouds and includes formulations for the autoconversion of cloud water into rainwater, the accretion of cloud droplets by falling raindrops, and the evaporation of falling raindrops (Pal et al. 2005).

Subgrid variability of clouds is accounted for by linking the average grid cell relative humidity to the cloud fraction and cloud water in the grid cell (Pal et al. 2000). The fractional cloud cover is expressed in terms of relative humidity RH as

$$FC = \sqrt{\frac{RH - RH_{\min}}{RH_{\max} - RH_{\min}}},$$
(5.1)

where  $RH_{min}$  is the relative humidity threshold at which clouds begin to form, and  $RH_{max}$  is the relative humidity where FC reaches unity. FC is assumed zero when RH is less than  $RH_{min}$  (80% for land and 90% for ocean) and unity when RH is greater than  $RH_{max}$  (101%).

The formation for the autoconversion of cloud water,  $Q_c$ , into precipitation, P, is given by

$$P = C_{ppt} \left(\frac{Q_c}{FC} - Q_c^{th}\right) FC , \qquad (5.2)$$

where,  $Q_c^{th}$  is the autoconversion threshold and is a function of temperature, and  $C_{ppt}$  is the autoconversion rate.

When precipitation is initiated, rain droplets falling through clouds collect and remove a portion of the cloud droplets through accretion. In addition, raindrops may evaporate as they fall through cloud-free air, especially in tropical and subtropical arid regions. To account for these processes, SUBEX includes simple formulations given by

$$P_{acc} = C_{acc} Q_c P_{sum}, \text{ and}$$
(5.3)

$$P_{evap} = C_{evap} (1 - RH) P_{sum}^{1/2},$$
(5.4)

where  $C_{acc}$  and  $C_{evap}$  are coefficients of accretion and evaporation, respectively, while  $P_{acc}$ ,  $P_{evap}$ , and  $P_{sum}$  are the amount of accreted cloud water, evaporated precipitation, and accumulated precipitation from above falling through the air, respectively. The implementation of this scheme in RegCM has been shown to improve substantially the simulation of precipitation, temperature, and other cloud-related variables over continental United States in summer (Pal. et al. 2000).

### 5.3.2 Convective Precipitation Schemes

This section provides a detailed description of the three convective schemes currently available for use in RegCM3.

### 5.3.2.1 Modified Anthes-Kuo Scheme

In the modified Anthes-Kuo scheme, precipitation is initiated when the moisture convergence, M, in a column exceeds a given threshold and the column is convectively unstable. A fraction of the total moisture convergence precipitates, depending on the mean columnar relative humidity, while the remaining fraction ( $\beta$ ) is redistributed throughout the column in proportion to the dryness at each vertical grid point in column. Latent heat of condensation is redistributed between cloud top and cloud bottom following a specified parabolic vertical heating profile, which yields maximum heating in the upper

half of the cloud layer (Anthes, 1977; Giorgi 1991; Giorgi et al. 1993b; Giorgi and Marunucci 1996).

In the standard scheme, moisture redistribution and condensation heat release occur instantaneously and produce excessively strong grid-point precipitation events. To suppress this numerical effect, Giorgi (1991) introduced a modification in which the latent heat of condensation and liquid water produced by cumulus convection are first accumulated and then released with a time constant on the order of the full lifetime of the cumulus cloud system. The precipitation amount produced by the modified Anthes-Kuo scheme is given by

$$P = M(1 - \beta), \text{ where}$$
(5.5)

$$\beta = \begin{cases} 2(1 - \overline{RH}) & \text{when } \overline{RH} \ge 0.5\\ 1 & \text{otherwise} \end{cases}$$
(5.6)

where *RH* is the average relative humidity of the sounding.

#### 5.3.2.2 Grell Scheme

Implementation of the Grell scheme (Grell 1993) is described in Giorgi et al. (1993c). The main points are highlighted below. In this scheme, clouds are pictured as two steady-state circulations caused by an updraft and a downdraft with no direct mixing between cloudy air and environmental air except at the top and bottom of the circulations. The mass flux in the updraft and downdraft ( $m_b$  and  $m_o$ , respectively) is assumed constant and the originating levels of the

updraft and downdraft are given by the levels of maximum and minimum moist static energy, respectively. The scheme is activated when a lifted parcel attains moist convection. Condensation in the updraft is calculated by lifting a saturated parcel. The downdraft mass flux ( $m_o$ ) depends on the updraft mass flux ( $m_b$ ) according to the following relation

$$m_o = \frac{\beta I_1}{I_2} m_b \tag{5.7}$$

where  $I_1$  is the amount of condensation integrated over the whole depth normalized by the updraft mass flux,  $I_2$  is the evaporation in the downdraft normalized by the downdraft mass flux, and  $\beta$  is the fraction of updraft condensate that reevaporates in the downdraft. Rainfall, P, is given by

$$P = I_1 m_b (1 - \beta) \,. \tag{5.8}$$

Due to the simplistic nature of the Grell scheme, several closure assumptions can be adopted to relate the mass flux at the bottom of the updraft to the largescale forcing. RegCM3's default version directly implements the quasiequilibrium assumption of Arakawa and Schubert (1974). It assumes that convective clouds stabilize the environment as fast as nonconvective processes destabilize it. For the Arakawa and Schubert (1974) closure, the updraft mass flux is given by

$$m_b = \frac{ABE'' - ABE}{\Delta t NA} \tag{5.9}$$

where *ABE*" is the production of available buoyant energy by the large-scale motions during the time step  $\Delta t$ , *ABE* is the amount of buoyant energy available to a cloud, and *NA* is the rate of change of available buoyant energy per unit  $m_b$ . The difference *ABE*"–*ABE* can be thought as the rate of destabilization over time  $\Delta t$ .

Another stability based closure assumption used in RegCM3 is similar to that implemented by Fritsch and Chappell (e.g., Giorgi et al. 1993a). This closure assumes that clouds remove the available buoyant energy in a given time scale, yielding the updraft mass flux

$$m_b = \frac{ABE}{\tau NA} \tag{5.10}$$

where  $\tau$  is the *ABE* removal timescale.

### 5.3.2.3 MIT Scheme

The MIT scheme (Emanuel 1991; Emanuel and Živković-Rothman 1999) is the newest cumulus convection option available in the RegCM3 (Pal et al. 2005). The scheme attempts to reflect the inhomogeneity of convective clouds by considering convective fluxes based on an idealized model of subcloud-scale updrafts and downdrafts. It attempts to represent the collective effects of an ensemble of individual O(100 m)-scale drafts, which accomplish much of the vertical transport in convective clouds, as opposed to ensembles of O(1km)-scale clouds. It assumes that mixing in clouds is highly episodic and inhomogeneous, rather than continuous as in the entraining plume model.

Convection is triggered when the first level of neutral buoyancy for undiluted, reversible ascent of near-surface air is greater than the level of cloud base. Between these two levels, air is lifted and a fraction of the condensed moisture forms precipitation while the remaining fraction forms the cloud

$$l_c = (1 - \varepsilon) l_a \,, \tag{5.11}$$

where  $l_c$  is the cloud water mixing ratio and  $l_a$  is the adiabatic liquid water content, and  $\varepsilon$  is the fraction of the condensed water converted to precipitation.

Air that is mixed into a cloud from the environment is assumed to form a spectrum of mixtures of differing mixing fraction, which then ascend or descend to their respective levels of neutral buoyancy. The fraction of the total cloud base mass flux,  $M_b$ , that mixes with its environment at any level is set to be proportional to the rate of change with altitude of the undiluted buoyancy

$$\frac{\delta M}{M_b} = \frac{\left|\delta B\right| + \Lambda \,\delta P}{\sum_{i=1}^N \left(\left|\delta B\right| + \Lambda \,\delta P\right)},\tag{5.12}$$

where  $\delta M$  is the rate of mixing of undilute cloud air,  $M_b$  is the net upward mass flux through cloud base,  $\Lambda$  is a mixing parameter, B is the buoyancy of undiluted cloud air,  $\delta B$  is the change in undilute buoyancy over a pressure interval  $\delta P$ , and N is the number of model levels.
The net upward mass flux  $M_b$  of undiluted air through cloud base is obtained from

$$\frac{\partial M_{b}}{\partial t} = \frac{\alpha}{\Delta t} \left( T_{\rho p} - T_{\rho} + \Delta T_{k} \right)_{LCL} - \frac{D}{\Delta t} M_{b} , \qquad (5.13)$$

where  $\alpha$  is a fixed parameter,  $T_{\rho\rho}$  is the density temperature of a parcel lifted adiabatically from the subcloud layer,  $T_{\rho}$  is the environmental density temperature, D is mass flux damping rate, and  $\Delta t$  is the time step, which is used to normalize  $\alpha$  and D. In the equation,  $\Delta T_k$  is a specified temperature deficit at the Lifting Condensation Level (LCL), which accounts for the ability of boundary layer turbulence to overcome negative buoyancy at the LCL.

The fraction of condensed water that is converted to precipitation is determined by converting to precipitation all cloud water in excess of a threshold water content within each sample of cloud air. Ice processes are crudely accounted for by allowing this threshold water content ( $l_{th}$ ) to be temperature dependent, such that

$$l_{th} = \begin{cases} l_o & T \ge 0^o C \\ l_o (1 - \frac{T}{T_{crit}}) & T_{crit} \le T \le 0^o C \\ 0 & T < T_{crit}, \end{cases}$$
(5.14)

where  $l_o$  is a warm cloud autoconversion threshold and  $T_{crit}$  is a critical temperature ( $^{o}C$ ) below which all cloud water is converted to precipitation. The surface precipitation rate, *P*, is given by

$$P = g^{-1}\omega_T l_p \sigma_d \tag{5.15}$$

where *g* is the acceleration due to gravity,  $\omega_T$  is the terminal velocity,  $l_p$  is the precipitation mixing ratio, and  $\sigma_d$  is the fractional area occupied by unsaturated downdraft.

The precipitation mixing ratio is determined from a conservation equation involving the rate of detrainment of precipitation from the updraft and the loss of precipitation by evaporation for each model layer. The fixed parameters used by the scheme have been optimized to produce the best possible forecasts of tropospheric relative humidity and temperature using a Single-Column Model (SCM). The SCM was driven by data from the intensive flux array operated in the western equatorial Pacific from 1 November 1992 to 28 February 1993 as part of the Tropical Ocean Global Atmosphere Coupled Ocean–Atmosphere Research Experiment (TOGA COARE) (Emanuel and Živković-Rothman 1999).

Pal et al. (2005) ascribe several advantages to the MIT scheme compared to other RegCM3 convection schemes. They note that in addition to the more physical representation of convection, it includes a formulation of the autoconversion of cloud water into precipitation inside cumulus clouds and involves ice processes by allowing the auto-conversion threshold water content to be temperature dependent. Another advantage is that the precipitation is added to a single, hydrostatic, unsaturated downdraft of assumed constant horizontal cross section. This downdraft transports heat and water substance, and precipitation evaporates according to a standard rate equation.

# 5.4 Sensitivity Experiments

The first goal of this study is to customize the RegCM3 to reproduce realistic amounts and spatial patterns of observed precipitation for the Horn of Africa. The customization focuses on testing and tuning the convection schemes as convection not only affects precipitation but also exerts significant influence on the evolution of mesoscale and even synoptic-scale circulation systems by distributing latent and sensible heat in the vertical (Anthes 1977). In addition, since one of the major purposes of the study is to enhance our knowledge of the causes of droughts and occasional floods the region experiences, the customization must also reasonably capture the observed interannual rainfall variability. For all model sensitivity experiments in this section, the RegCM3 available before the recent release (May 2006) was used because most of the sensitivity experiments were performed prior to May 2006. However, the RegCM3 released in May 2006 is used to examine the ability of the model to capture the observed interannual rainfall variability in Section 5.5 and to investigate the effects of SST and local vegetation coverage on the Horn of Africa rainfall in Chapter 6. The changes in the new release were geared towards improving RegCM3's capabilities and user-friendliness. In this regard, the dynamical code was modified for parallel computing and new interfaces were added for a variety of reanalysis and GCM boundary conditions. The RegCM3 also now operates on different computer platforms (http://www.ictp.trieste.it/RegCNET/regcmbeta.pdf).

# 5.4.1 Experimental Design and Model Physical Characteristics

Following the discussion in Section 5.2, the model physical characteristics were selected carefully. The model domain is centered on the Horn of Africa and is chosen to cover most of Africa and the western Indian Ocean (Fig. 5.1). It encompasses the main monsoon systems that affect Horn of Africa weather. The model is based on a Mercator conformal projection with a domain size that extends 7080 km in the zonal direction and 6960 km in the meridional direction. The choice of the domain with boundaries far from the study region and largely over ocean areas ensures that relevant atmospheric and oceanic forcings are included. It also avoids problems arising from the mismatch between the resolution of the model and the forcing data near the boundaries (Giorgi et al. 1996), as described in Section 5.2.

The model includes 18 levels in the vertical. The vertical levels are spaced such that the highest concentration is near the surface. A 3-minute time step is used for model integration. For model resolution, Sun et al. (1999) ran RegCM2 over a large domain over East Africa using horizontal resolutions ranging from 50 to 100 km and found acceptable results for all experiments. For our experiments, the default 60-km horizontal resolution therefore is used.



FIGURE 5.1. Region shown is the total domain, with surface elevation shaded (m).

For climate studies, a long simulation period is appropriate instead of individual short durations that are relevant for studying weather events (e.g., Giorgi 1991). To test the performance of RegCM3 for the Horn of Africa during the monsoon season, the model was integrated from 25 June to 31 August. The model was initialized and driven by the NCEP/NCAR Reanalysis version 1 data set (Kalnay et al. 1995) and the NOAA Optimum Interpolation (OI) SST (OISST) monthly data (Reynolds et al. 2002). The atmospheric lateral boundary conditions, which include horizontal winds, temperature, surface pressure, and water vapor were supplied at 6 hr intervals over a 720 km buffer zone. The first five days of the simulation were considered model spin up and discarded, and the simulations for July and August were used for model evaluation.

The default model configuration was run with the four convective schemes discussed in Section 5.3—the modified Anthes-Kuo scheme (Kuo), the MIT scheme (MIT), the Grell scheme with the Arakawa-Schubert closure (GrAS), and the Grell scheme with Fritsch-Chappell closure (GrFC). For each convective scheme, two simulations were performed for contrasting summer seasons over the Horn of Africa.

The two prominent contrasting summers previously investigated for Ethiopia are the recent wet season of 1996 and one of the driest seasons of 1984 (Segele and Lamb 2005). Simulated rainfall rates for these years were compared with Ethiopian raingauge data (Segele and Lamb 2005; Chapter 3), the Climate Prediction Center (CPC) Merged Analysis of Precipitation (CMAP) data (Xie et al. 1997), and the Climate Research Unit (CRU) data set (New et al. 2000). The CRU data set contains historical monthly precipitation for global land areas from 1901 to 2000, gridded at 0.5° resolution. The data was obtained from the ICTP website at http://www.ictp.trieste.it/~pubregcm/RegCM3/globedat.htm.

## 5.4.2 Spatial Patterns of Simulated Precipitation

The model performance is evaluated by comparing July-August simulated precipitation with the corresponding observed pattern shown in Fig. 5.2. The main reason for choosing July and August is that much of the summer rain over the Horn of Africa occurs during these peak-season months. Moreover, the overall quality of the Kiremt season depends largely on the amount of rainfall and its distribution during July-August. For example, Segele and Lamb (2005) noted that the largest rainfall deficiencies/excesses in 1984/1996 typically occurred during August over many areas. Thus, evaluating the model performance for July-August for the extreme 1984 and 1996 seasons is sufficient to assess the accuracy of the simulations and the ability of the model to capture the interannual rainfall variations.

In addition, because rainfall is the major climate element of significant socioeconomic impact and because one of the most important sources of errors in RCMs is associated with precipitation schemes (Pal et al. 2005), the performance of the model is evaluated by assessing only the ultimate outcome of the simulated precipitation. In this section, the spatial distributions of the simulated rainfall rates and differences between simulated rainfall rates for dry and wet years are compared qualitatively with the respective observed/satellite estimated data sets. A thorough quantitative evaluation follows in Section 5.4.3.



FIGURE 5.2. Maps of observed July-August rainfall rates (mm d<sup>-1</sup>) for 1984 (left) and 1996 (right) based on the Climate Research Unit (CRU) data set (top) and CMAP analysis (bottom). Insets in the top panel show observed station rainfall rates for northern two-thirds of Ethiopia computed by dividing July-August total rainfall amount by 62 days. The southern and southeastern regions of Ethiopia, which do not receive rainfall during the peak of the summer season, are unshaded in the insets. Contours are drawn at intervals of 5 mm d<sup>-1</sup>.

# 5.4.2.1 Observed Rainfall Patterns

Figure 5.2 shows the observed July-August rainfall rates for 1984 and 1996 for the CRU, CMAP, and Ethiopian raingauge data sets. The CRU and CMAP

data sets locate the major centers of rainfall maxima over Ethiopia, Central Africa, and Nigeria. Except over Nigeria, where the CRU data indicate wetter conditions in 1984, both the CRU and CMAP data sets show wetter conditions in 1996 than 1984 over most areas. Note the expansion of the 5 mm d<sup>-1</sup> contour into eastern Ethiopia, southern Sudan and Chad, and northern Nigeria in 1996.

Over Ethiopia, both the CRU and CMAP data sets underestimate the hgh resolution raingauge-based pattern in both 1984 and 1996, especially over western Ethiopia. The underestimation is higher for CMAP data in 1984. Considering the low resolution of the CMAP data and the limited number of stations employed in the CRU analysis, these differences between Ethiopian raingauge and the CRU and CMAP analyses is to be expected. On a large-scale, both the CRU and CMAP data sets can be considered to represent the observed rainfall patterns adequately. Although all three data sets will be used to evaluate simulated precipitation, only departures from CMAP are shown in Figs. 5.3-5.7 due to the oceanic coverage the CMAP data provide.

# 5.4.2.2 Simulated Rainfall Based on the Modified Anthes-Kuo Convective Scheme

The simulation with the modified Anthes-Kuo scheme (Fig. 5.3) showed rainfall maxima only over the Horn of Africa and failed to reproduce the heavy observed rainfall over southern Nigeria and central Indian Ocean in 1984. For



FIGURE 5.3. July-August simulated rainfall rates (top) and departures from the Climate Prediction Center (CPC) Merged Analysis of Precipitation (CMAP) data (bottom) for Dry 1984 (left) and Wet 1996 (right) for default model configuration with the modified Anthes-Kuo scheme. Units are mm d<sup>-1</sup>.

that season, it greatly underestimated rainfall in most regions, especially over the Gulf of Guinea, the Congo basin, and over central Indian Ocean, and also overestimated rainfall over Ethiopia and Yemen highlands. For 1996, the scheme

produced weak rainfall maxima over Nigeria and Sudan. Farther east, the scheme simulated widespread rainfall across the highlands of Ethiopia and Yemen. Except in a few localities, simulated rainfall rate departures from CMAP and CRU were relatively small over Ethiopia during the summer of 1996.

In general, the modified Anthes-Kuo scheme tends to underestimate rainfall rates for most places, with significant deficiencies especially over the Gulf of Guinea, the Congo basin, and the central equatorial Indian Ocean, but produces widespread and heavy rainfall over the mountainous regions. The failure of the model to reproduce correctly the rainfall over the Gulf of Guinea regions (especially Nigeria) and central Indian Ocean may be related to their location near the boundaries of the model domain (Section 5.2).

The large errors in the interior of the domain, especially over the Central African Republic/the Democratic Republic of the Congo and, in 1996, over eastern Sudan/southwestern Ethiopia, may be related to the scheme's deficiency in representing convection. For example, the scheme does not capture important stabilizing mechanisms such as low-level drying by downdrafts and cooling by rain and cloud evaporation. In addition, the specified parabolic vertical heating profile and moisture convergence parameter may not be realistic (Giorgi 1991). Despite its weakness over central and western Africa, the modified Anthes-Kuo scheme produces reasonable rainfall rates over most parts of Ethiopia.

#### 5.4.2.3 Simulated Rainfall Based on the MIT Convective Scheme

The simulation with the MIT scheme produced excessive rainfall rates everywhere in the model domain except over the Gulf of Guinea, the central equatorial Indian Ocean and at few localities over southern Sudan (Fig. 5.4). In 1984, the simulation failed to reproduce the heavy rainfall center over southern Nigeria (Fig. 5.2) and produced rainfall rates exceeding 15 mm d<sup>-1</sup> over a large area over Central Africa, Ethiopia, and the Yemen highlands. In 1996, the model reproduced observed centers of precipitation maxima and patterns over Nigeria, Chad, Sudan, and Ethiopia, but greatly exceeded observed rainfall rates almost everywhere.

Leaving aside problems of spurious precipitation occurring near model boundaries, the major deficiency of the scheme appears to be the production of excessive rainfall over most regions. Pal et al. (2005) also noted that the MIT scheme tends to generate excessive precipitation over particularly wet areas. In addition, although meager in amount, it produced rainfall over regions that receive no rain during the peak of the summer season (e.g., southern and southeastern Ethiopia). On the positive side, and in contrast to the simulation results of the modified Anthes-Kuo scheme, the MIT scheme better locates the major precipitation centers.



FIGURE 5.4. Same as Fig. 5.3 except for the MIT scheme.

The excessive rainfall rate the MIT scheme produces might be related to the fact that the scheme was tuned over oceanic areas. As indicated earlier, the overall performance of the scheme was evaluated using the TOGA COARE data over the western equatorial Pacific Ocean. The parameters were optimized to produce the smallest root mean square error between observed and predicted tropospheric relative humidity (Emanuel and Živković-Rothman 1999).

#### 5.4.2.4 Simulated Rainfall Based on the Grell Convective Scheme

The simulations with the Grell scheme produce centers of precipitation maxima and surrounding spatial patterns reasonably well for both closure assumptions, with isolated areas of overestimation scattered over the continent. However, there are large and contiguous regions where the model significantly overestimates rainfall, especially over the margins of the tropical rainbelt in both 1984 and 1996 (Figs. 5.5, 5.6). The main convection belt also is located slightly north its observed position in Fig. 5.2.

The GrAS simulation (Fig. 5.5) produced rainfall rates that compare well with observations over the eastern domain extending from Sudan to Ethiopia in 1984, although there are pockets of excessive rainfall rates over mountainous locations in Ethiopia and Yemen. Simulated rainfall rates are much lower than observed over the western domain extending from the Central African Republic to the Congo basin, and like most of the other simulations, near the peripheries of the model domain.

In 1996, the GrAS scheme correctly simulated the major centers of rainfall maxima over Ethiopia, Central Africa, and Nigeria. Rainfall rate departures from CMAP patterns are relatively low over most areas, but larger rainfall rates were simulated over Nigeria, the Yemen highlands, and a large expanse across the western Indian Ocean. Lower rainfall rates are simulated primarily on the southern edge of the monsoon rain belt, especially over the Congo basin.



FIGURE 5.5. Same as Fig. 5.3 except for the Grell scheme with the Arakawa-Schubert (GrAS) closure.

The GrFC simulation (Figs. 5.6) produced heavy rainfall especially over Central Africa and the Gulf of Guinea, but simulated well-defined centers of rainfall maxima. In 1984, the GrFC scheme overestimated rainfall over the northern parts of the monsoon rain belt with rainfall rate departures in excess of 10 mm d<sup>-1</sup> over southern Sudan and the highlands of Ethiopia and Yemen, and underestimated rainfall over the Congo basin. In 1996, the scheme produced excessive rainfall rates over the Gulf of Guinea, southern Chad, western Ethiopia, and the Yemen highlands, and over the western Indian Ocean. Except near the edges of the domain, negative departures are generally small.

Comparison of Figs. 5.5 and 5.6 shows that the GrAS simulation produces lower rainfall rates and more widespread and larger negative departures than the GrFC simulation. The Arakawa-Schubert closure minimizes convective activity since it forces dissipation of large-scale buoyant energy production within a single model time step, while the Fritsch-Chappell-type closure accumulates the buoyant energy for a specified time before removing it and so tends to increase the amount of convective rain (Giorgi and Shields 1999). Although we chose to show model departures from CMAP estimates due to their oceanic coverage, the overall assessment remains the same when simulated precipitation is compared with the CRU data. The differences and similarities of the CRU, CMAP, and the Ethiopian raingauge data sets were summarized in Section 5.4.2.1.



FIGURE 5.6. Same as Fig. 5.3 except for the Grell scheme with Fritsch-Chappell (GrFC) closure.

# 5.4.2.5 Interannual Variations

To document further how well the various schemes reproduce the interannual variation between the two years, the observed difference between the rainfall for the two years (1996 minus 1984, Figs 5.7, 5.8) is used as

benchmark against which to compare counterpart differences from the simulations (Fig. 5.9). The observed rainfall difference for July-August (Fig. 5.7) shows that 1996 was much wetter than 1984 over the Horn of Africa, Chad, Central African Republic, and northern Nigeria. Examination of the CRU and CMAP analyses shows that the excess rainfall in 1996 was primarily on the northern parts of the summer tropical rain belt while drier conditions border the southern edge. This also is reflected in Ethiopian raingauge analysis, which reveals wetter conditions over southwestern Ethiopia in 1984.



FIGURE 5.7. Difference in observed rainfall rate (1996 minus 1984) for July-August. (**a**) CRU data set and raingauge data (inset) for the northern two-thirds of Ethiopia. White shading in the inset (for rainfall rate difference between -1 and +1 mm d<sup>-1</sup>) is valid only for the non-hatched region. (**b**) CMAP analysis. Units are mm d<sup>-1</sup>.

There are some discrepancies between the CRU and CMAP analyses as well as between the Ethiopian raingauge (Fig. 5.7, inset) and the CRU data. Compared to both the CRU and Ethiopian raingauge analyses, the CMAP data overestimate rainfall over western and northern Ethiopia and locate the center of the maximum difference much to the north in Ethiopia. A noticeable discrepancy between the CRU and CMAP data also appears over southern Sudan and parts of Chad, where the CRU data show negative or isolated areas of positive differences, but the CMAP analysis exhibits extended wetter conditions in 1996. The CRU data capture the center of maximum difference over central Ethiopia, although they diminish the magnitude of the rainfall difference between the two years. The CRU data also do not reflect the isolated weak negative (positive) difference over southwestern (eastern) Ethiopia. Clearly, this is a result of the large number of stations used in the Ethiopian raingauge data analysis. In general, however, there is good agreement among the three precipitation data sets in terms of spatial patterns and locations of rainfall maxima in 1984 and 1996.

The difference between the two seasons is seen most clearly on a monthly basis, with August being exceedingly dry/wet in 1984/1996 (Fig. 5.8) compared to the corresponding July (not shown). In fact, August 1984 was so dry that there were massive crop failures over much of northern and northeastern Ethiopia. In contrast, in August 1996, heavy monsoon rainfall caused large-scale floods over much of central Ethiopia. These situations are reflected in the CRU data (not shown), but more so in the CMAP monthly analysis (Fig. 5.8). In August 1996,

the 5 mm d<sup>-1</sup> contour covers western and central Eritrea and almost the entire Kiremt regions of Ethiopia except the far east areas bordering Djibouti. In August 1984, on the other hand, the 5 mm d<sup>-1</sup> contour is limited to an isolated area over western Ethiopia, leaving substantial portions of Ethiopia under dry conditions (1-2 mm d<sup>-1</sup>). Whether the RegCM3 is capable of identifying such extreme contrasts between these two summers is qualitatively assessed below.



FIGURE 5.8. Analysis of CMAP estimates for August for Dry 1984 (left) and Wet 1996 (right). Units are mm d<sup>-1</sup>.

The wetter conditions over the northern parts of the monsoon rain belt in 1996 (Fig. 5.7) are reflected in all simulations, especially when the modified Anthes-Kuo and the MIT convection schemes are used (Fig. 5.9a, b). The modified Anthes-Kuo scheme simulated wetter conditions in 1996 throughout



FIGURE 5.9. Difference in simulated rainfall rate (1996 minus 1984) for July-August. (**a**) Modified Anthes-Kuo scheme. (**b**) MIT scheme. (**c**) Grell scheme with the Arakawa-Schubert (GrAS) closure. (**d**) Grell scheme with Fritsch-Chappell (GrFC) closure. Units are mm d<sup>-1</sup>.

the domain except over a few areas in central Ethiopia, the Central African Republic, and the Indian Ocean. However, except over western Eritrea and isolated areas of Ethiopia, the simulation with the Anthes-Kuo scheme did not produce the correct interannual rainfall variability over much of the Horn of Africa, southern Chad, Central African Republic, and the Gulf of Guinea (Figs. 5.7, 5.9a).

The simulation with the MIT scheme, on the other hand, shows extensive areas of wetter conditions over northern regions of the monsoon rainbelt and drier conditions over parts of the coastal regions of the Gulf of Guinea and southern Sudan in 1996. Although not a perfect match to the observed difference, only the MIT scheme produced drier conditions over parts of the coastal regions of the Gulf of Guinea and significant excesses over parts of Ethiopia in 1996. The scheme also produced drier conditions over southwestern Ethiopia in 1996 (Fig. 5.9b) in good agreement with station-based analysis (Fig. 5.7, inset). The major weaknesses as in the MIT scheme are the deficient (excessive) simulated rainfall in 1996 (1984) over the Central African Republic, where both CMAP and CRU indicate positive rainfall differences. However, this scheme has correctly identified the negative difference over southern Sudan and northern portions of the Democratic Republic of the Congo (Figs. 5.7a, 5.9b).

The GrAS simulation produced wetter conditions over large parts of the monsoon rainbelt from about 5°-10°N in 1984 than 1996, with isolated pockets of positive difference over the northern parts of the monsoon rain belt (Fig. 5.9c). In particular, except for a few locations in Eritrea and northeastern Ethiopia, the

scheme failed to show the correct interannual variability over most parts of the Horn of Africa and the coastal regions of the Gulf of Guinea (Fig. 5.7a, b). In contrast to observations (Fig. 5.7a, b), the GrAS simulation difference indicates wetter conditions in 1984 and drier conditions in 1996 over much of central and western Ethiopia. The scheme also does not identify the observed dry (wet) conditions in 1996 (1984) over Cameroon and Gabon (Figs. 5.7, 5.9c).

The GrFC scheme simulates the interannual variability over northern Ethiopia better than GrAS (Fig. 5.9d), but fails to reproduce the large positive difference over the Horn of Africa as indicated by CRU and CMAP data (Fig. 5.7). In particular, the scheme simulated drier (wetter) conditions in 1996 (1984) over parts of south-central Ethiopia, in direct contradiction to the observed wetter (drier) conditions in 1996 (1984). It also fails to show the correct sign of interannual variability over southern Sudan and the Gulf of Guinea regions (Fig. 5.9d).

Over the equatorial Indian Ocean, all schemes (Fig. 5.9) indicate drier (wetter) conditions in 1984 (1996). The CMAP analysis, however, shows wetter conditions in 1996 than in 1984 over much of the Indian Ocean (Fig. 5.7b). In addition, unlike the CMAP analysis (Fig. 5.7b), all schemes indicate excessive rainfall over Nigeria and the Gulf of Guinea in 1996.

In summary, RegCM3 produces wide-ranging precipitation distributions and amounts when the different convective schemes are used. The Anthes-Kuo scheme captures the rainfall maxima over Ethiopian highlands but greatly underestimates rainfall elsewhere. The MIT scheme captures the rainfall patterns and centers of precipitation maxima over continental Africa but substantially overestimates the rainfall rates over most areas. On the positive side, the MIT scheme captures the interannual variability better than the other schemes. The Grell scheme fails to identify the correct signs of the interannual variations, producing wetter conditions when it was dry and vice versa. Thus, the simulations performed using all schemes employed in the RegCM3 show several deficiencies. These weaknesses include producing either excessively abundant or deficient rainfall amounts, failing to identify the correct signs of the interannual variations, and mislocating the major centers of rainfall maxima, thus failing to produce the correct rainfall distributions. As it stands, the model cannot reasonably be used with the above deficiencies for quality climate studies over the Horn of Africa. The above qualitative assessments are further supported by quantitative error analyses discussed in the next section.

## 5.4.3 Regional Performance of RegCM3 for the Default Configuration

The performance of RegCM3 over different monsoon regions (Fig. 5.10) for 1984 and 1996 now is examined quantitatively by analyzing the bias, root mean square error, and threat scores of the simulations relative to observations. For



Figure 5.10. Map showing model domain and the areas for which error analyses are performed. The large domain resides 20 grid points (1200 km) inside the model boundary to capture interior model features.

precipitation, *P*, the bias is a time average of the error defined as

$$bias = \frac{\sum_{i} (P_i^M - P_i^O)}{N},$$
(5.16)

and the root mean square error, RMSE, is defined as the time average of

$$rmse = \left(\frac{\sum_{i} \left(P_{i}^{M} - P_{i}^{O}\right)^{2}}{N}\right)^{1/2}.$$
(5.17)

where the summation is carried out over *N* grid points in a predefined region and the superscripts *M* and *O* refer to model and observation. For verification of the model performance in reproducing spatial precipitation patterns, the threat score  $T_{pt}$  is used (e.g., Giorgi and Marinucci 1996). For precipitation threshold *pt*, the threat score is defined as

$$T_{pt} = \frac{C_{pt}}{O_{pt} + F_{pt} - C_{pt}},$$
(5.18)

where,  $O_{pt}$  is number of grid points with observed precipitation in excess of precipitation threshold pt,  $F_{pt}$  is the corresponding number for model precipitation, and  $C_{pt}$  is number of grid points with both observed and model precipitation exceeding pt. The threat score measures the accuracy of the model in forecasting the area that receives an amount of precipitation above a given threshold. It varies from 0 for no skill to 1 for a perfect forecast.

These statistical measures are applied over the different regions shown in Fig. 5.10 to evaluate model performance using July-August rainfall rates. The RMS error and threat scores are averaged over 1984 and 1996 to show the overall model performance, but the bias values are given for 1984 and 1996 separately. Although the CMAP, CRU, and Ethiopian station data are used for verification, only results obtained from the CMAP and Ethiopian station data are shown in Tables 5.1 and 5.2. Ethiopian station data are used for the innermost domain that encompasses all observation sites in Ethiopia that are used in this study, while CMAP and CRU data are used for all areas selected for error analyses (Fig. 5.10). Comparison of model and observed precipitation indicates that all four simulations give large RMSE and bias values (Table 5.1) relative to the observed rainfall amounts (e.g., Fig. 5.2). The RMS and bias error values generally decrease as the region of interest increases in size; they are large for Ethiopia and small for the large domain interior.

Table 5.1. Root mean square (RMS) error and bias values (mm d<sup>-1</sup>) for simulations calculated by comparison with Ethiopian station observations and CMAP analysis for regions defined in Fig. 5.10. The RMS error values are averages of 1984 and 1996 peak seasons (July-August). Bias values are shown separately for July-August 1984 and 1996. Except for column 1 (Ethiopia, stations), for which model rainfall rate was interpolated to station locations, the other statistics were computed after interpolating CMAP data onto model grids.

	Region															
Convection	Ethiopia		Ethiopia			East			Central			Large				
scheme	(Stations)		(CMAP)			Africa			Africa			Domain				
							(CMAP)			(CMAP)			(CMAP)			
	Ave.		ias	Ave.	Bias		Ave.	Bias		Ave.	Bias		Ave.	B	Bias	
	RMS	84	96	KM3	84	96	KM3	84	96	RMS	84	96	KM3	84	96	
Mod. Anthes- Kuo	3.2	0.8	-1.3	2.4	1.4	-1.4	2.5	0.7	-1.3	2.5	-1.1	-2.2	1.7	-0.3	-0.3	
MIT	9.4	7.8	7.1	8.7	6.8	4.4	7.0	5.3	3.1	7.3	6.8	5.8	3.5	1.5	1.5	
Grell (AS)	3.8	2.6	-0.9	3.4	2.3	-0.9	3.2	1.8	-0.8	2.3	0.3	-1.4	1.8	0.1	-0.1	
Grell (FC)	5.1	4.1	2.7	5.4	4.6	2.3	4.8	3.6	2.0	5.6	4.0	3.3	2.5	0.7	0.5	

Statistically, the simulation with the modified Anthes-Kuo scheme performs very well, having the lowest RMS error values and relatively low departures, but largely overestimates rainfall over Ethiopia and East Africa in 1984 and underpredicts precipitation over all regions in 1996 (Table 5.1). This is consistent with the qualitative assessment of the spatial rainfall patterns discussed in Section 5.4.2.2 (Fig. 5.3). However, the low RMS and bias error values of the modified Anthes-Kuo scheme compared to the other schemes should not conceal its deficiency in reproducing the observed rainfall distributions and its inadequacy in identifying the correct sign of the interannual variability, especially over the Horn of Africa and central and western Africa.

The MIT scheme gives the highest RMS errors and largest positive bias for all regions and thus excessively overestimates rainfall (Table 5.1). For Ethiopia, both the RMS and bias are large compared to the other domains. One reason for this anomaly is the small domain size for Ethiopia. It might also be linked to the model's overestimation of orographic effects (Pal et al. 2005). The RMS computed relative to Ethiopian raingauge data is even larger and exceeds the average rainfall rate, especially over eastern regions. The large RMS and bias values are consistent with the qualitative discussion in Section 5.4.2.3. However, these statistics should be weighed against the advantage the MIT scheme offers. It was noted that the MIT scheme captures the correct sign of the interannual variability over much of the model domain better than any of the other schemes do. This

important quality should be considered when customizing the model for the Horn of Africa.

The GrAS scheme produces precipitation with the lowest bias in 1996 over the selected regions, but overestimates rainfall in 1984 especially over Ethiopia (Table 5.1). Compared to the modified Anthes-Kuo scheme, the GrAS scheme has larger RMSEs over all domains, but shows little bias over the Large Domain. But, note that the GrAS scheme did not adequately produce the observed rainfall distributions and amounts in both 1984 and 1996, and it greatly underestimated rainfall over much of the domain (Fig. 5.5). The GrAS scheme also failed to identify the correct sign of the interannual variability over most areas (Fig. 5.9c).

Next to the MIT scheme, the GrFC possesses the largest RMSE and bias values. The scheme highly overestimates rainfall over all selected domains in 1984 (Fig. 5.1). The largest average error of the scheme occurs over Central Africa, in contrast to the other schemes which give the largest errors over Ethiopia. However, the GrFC still exhibits the largest bias over Ethiopia in 1984. Furthermore, examination of the errors reveals that the GrFC performs worse than the GrAS. Noting further that the GrFC was unsuccessful in reproducing the observed rainfall amounts and distributions and identifying the correct sign of the interannual variations over Ethiopia (Fig. 5.9d), the scheme appears

incapable of producing quality simulations appropriate for climate studies over the Horn of Africa.

Model bias and RMSE values are larger for Ethiopia for the Kuo, GrAS, and MIT schemes when station data are used for the verification, but are relatively small when compared to the CMAP data for that country. The large model bias and RMSE for station data may be due to the large spatial inhomogeneity of Ethiopian rainfall and the inability of a regional climate model to capture smallscale details. The bias and RMSE of CMAP/CRU relative to the Ethiopian raingauge data also are relatively large. For example, the average RMSE between CMAP (CRU) and Ethiopian station rainfall is 2.5 (2.4) mm d<sup>-1</sup>. In addition, both the CRU and CMAP data show negative biases when compared to observed station data for Ethiopia, which likely is a reflection of the large amount of smoothing in the CMAP and CRU analyses, the low resolution of CMAP, and the limited number of observing stations used in CRU. However, since the Ethiopian raingauge data give the best estimate of "truth" in representing the local rainfall amounts and distributions, it should be used to assess the quality of the simulations.

The RegCM3 generally does well in reproducing the observed spatial patterns for very low rainfall rates (0.1-2 mm d<sup>-1</sup>), with threat scores exceeding 0.8 for all convective schemes relative to Ethiopian raingauge data (not shown).

The threat scores for rainfall exceeding 2.0 and 3.0 mm d<sup>-1</sup> are shown in Table 5.2. The high threat scores for these small rainfall thresholds indicate that in both the model and observations most places received some precipitation during the simulated months. The scores generally decrease as the threshold increases. These scores are relatively large for Ethiopia due to the small number of stations (100), but become smaller as the size of the computational area increases. All the convective schemes produce comparable threat scores, but the MIT scheme performs better over the large domain. The threat scores drop significantly for thresholds exceeding 5.0 mm d<sup>-1</sup> (not shown). All computed threat scores are much higher than the monthly threat scores calculated for application of RegCM to Europe for January and July conditions (e.g., Giorgi and Marinucci 1996), but this may be a result of the longer integrations (two months) in our study.

In general, the modified Anthes-Kuo and GrAS schemes outperform both the GrFC and MIT schemes statistically, but have serious shortcomings in identifying the interannual variations and in reproducing the observed spatial rainfall distributions. The GrFC simulations also share these shortcomings. The excessive rainfall the MIT scheme produces is the main cause for the large RMSE and bias values. In fact, the RMSE of the MIT scheme is larger than the average observed rainfall rate for Ethiopia. However, in spite of the excess rainfall the MIT scheme produces, it outperforms the other schemes by reasonably reproducing the centers of rainfall maxima and by identifying the correct signs of

the interannual rainfall variations over large portions of model domain. The large threat scores of the MIT scheme, especially for Ethiopia and the Large Domain (Table 5.2), also demonstrate the higher skills of the scheme.

Table 5.2. Threat scores for July-August simulated rainfall for the different convective schemes relative to Ethiopian raingauge and CMAP data. The threat scores are computed for regions defined in Fig. 5.10 for rainfall amounts exceeding a given threshold value. The scores shown here are for 2 and 3 mm  $d^{-1}$  thresholds (i.e., threat scores are for rainfall > 2 mm  $d^{-1}$  and > 3 mm  $d^{-1}$ , respectively). The values shown are averages of 1984 and 1996 peak seasons (July-August). Except for column 1 (Ethiopia, stations), for which model rainfall rate was interpolated to station locations, the other statistics were computed after interpolating CMAP data onto model grids.

	Region										
Convection scheme	Ethiopia (Stations)		Ethiopia (CMAP)		East Africa (CMAP)		Central Africa (CMAP)		Large Domain (CMAP)		
	Thresholds (mm)							n)			
	2	3	2	3	2	3	2	3	2	3	
Modified Anthes-Kuo	0.93	0.80	0.89	0.81	0.75	0.54	0.88	0.48	0.48	0.30	
MIT	0.94	0.82	0.87	0.79	0.76	0.67	0.89	0.76	0.59	0.62	
Grell (AS)	0.95	0.82	0.84	0.76	0.78	0.66	0.91	0.74	0.48	0.43	
Grell (FC)	0.94	0.82	0.86	0.78	0.80	0.69	0.89	0.79	0.55	0.56	

Combining the positive aspects of the schemes reflected in the qualitative evaluation described in the previous section and to some extent in quantitative evaluation above (threat scores), the MIT scheme was chosen for further application of RegCM3 over the Horn of Africa. The modified Anthes-Kuo scheme was excluded, despite its strong statistical qualities, because of the serious shortcomings discussed above. On the other hand, in spite of its poor statistical performance, the MIT scheme was selected for its ability to identify interannual rainfall variations and spatial patterns. In addition, the large bias and RMSE values of the MIT scheme easily can be corrected through model sensitivity experiments. The next section focuses on reducing the excessive bias/RMSE values that simulations with the MIT scheme produce.

#### 5.4.4 Adaptation of RegCM3 to Horn of Africa

Despite the excessive precipitation the MIT scheme produces, it captures the interannual rainfall variability over Ethiopia better than the other convective schemes. The MIT scheme also produces the spatial precipitation patterns well, especially for Ethiopia and the Large Domain shown in Fig. 5.10. Since capturing the correct sign of the interannual rainfall variations is critical for climate studies, the MIT scheme is chosen for further application and adaptation in the current research. Henceforth, efforts are made to reduce the excessive precipitation it produces without impacting the spatial distributions and interannual variability.

For MIT scheme, as noted in Section 5.3.2.3, the precipitation amount and the characteristics of the heating profile and moistening produced by the scheme are determined by (a) the relaxation rate  $\alpha$  (Eq. 5.13), (b) the warm cloud

autoconversion threshold  $l_0$  (Eq. 5.14), (c) the fraction of precipitation that falls outside of cloud  $\sigma_s$ , and (d) the fractional area occupied by unsaturated downdraft  $\sigma_d$  (Eq. 5.16). Each of these parameters now is reviewed briefly.

The parameter  $\alpha$  determines the rate of approach to statistical equilibrium. When  $\alpha$  is too small, convection may be underactive; when it is too large, the precipitation patterns may become noisy. Its default value is 0.2.

The fraction of condensed water converted to precipitation in an ascending updraft is a function of the total amount of condensate produced, the air temperature, the actual updraft velocity, and the type of precipitation falling through the updraft. In the scheme, the warm cloud autoconversion threshold l<sub>o</sub> (Eq. 5.14) determines the amount of cloud water available for precipitation conversion. Its default value is 0.0011 gm gm<sup>-1</sup>.

The main effect of  $\sigma_s$  is moistening the troposphere by evaporation, thereby increasing the moisture available for precipitation. However, its specification requires knowledge of the exact configuration of the cloud and presence of anvil. In the scheme, it is set to 0.12 at and above cloud base and 1.0 below it. The parameter  $\sigma_d$  appears in the conservation equation for precipitation and varies nearly inversely with the precipitation content. It also affects evaporation although weakly. Its default value is 0.05.

To obtain an improved simulated precipitation over the Horn of Africa, each of the above parameters was varied and the resulting simulated precipitation compared with observations. As summarized in Table 5.3, four sets of experiments were performed. In Experiment I, the combined effects of  $\sigma_d$  and  $\sigma_s$  were examined. For Experiments II and III, the parameter  $\alpha$  and the autoconversion threshold ( $l_o$ ), respectively, were varied while holding all the other parameters to their default values. In Experiment IV, the combined effects of  $\alpha$  and  $l_o$  were examined. For all experiments, the same model setup discussed in Section 5.4 was used. Table 5.3 gives the default and specified sets of values for each experiment.

The performance of the model for each experiment was evaluated quantitatively for the different regions shown in Fig. 5.10. The results for Experiments III and IV, which revealed clear advantage over the default simulations, are given in Table 5.4 and 5.5. All four simulations of Experiment I (not shown) affected the precipitation amount very little. Both model bias and RMSE are high especially for the Ethiopia, East Africa, and Central Africa domains (Fig. 5.10) when compared with both raingauge data and CMAP analysis. For these regions, the RMSE values vary from 6.7 to 9.1 mm d<sup>-1</sup> and the model bias becomes as large as 6.8 mm d<sup>-1</sup>. There generally is little advantage in these simulations compared to the default run. Experiment II also did not give satisfactory results (not shown). RMSE values were large, ranging from

	Experiment I		Experiment II	Experiment III	Experiment IV		
Default	Default $\sigma_d$ (0.05)values $\sigma_s$ (0.12)		α (0.2)	l <sub>o</sub> (0.0011)	a (0.2)	l <sub>o</sub> (0.0011)	
values							
Run 1	0.05	0.15	0.0002	0.0001	0.02	0.008	
Run 2	0.01	0.15	0.002	0.002	0.02	0.010	
Run 3	0.05	0.10	0.02	0.004	0.06	0.004	
Run 4	0.01	0.10	0.06	0.008	0.06	0.008	
Run 5	-	_	0.8	0.01	0.10	0.010	
Run 6	_	_	_	0.05	0.30	0.010	

Table 5.3. Summary of sensitivity experiments and specified values of model parameters for the MIT scheme.

5.5 mm d<sup>-1</sup> for Central Africa to 10.5 mm d<sup>-1</sup> for Ethiopia. The bias values generally were relatively small, especially for the large domain (0.2-1.1 mm d<sup>-1</sup>), but were large for Ethiopia (3.1-6.1 mm d<sup>-1</sup>). The effect of  $\alpha$  is more evident over the ocean, where high rainfall rates were simulated for low  $\alpha$  values. In addition, the spatial coverage of simulated precipitation significantly shrinks as  $\alpha$  decreases, especially over central parts of Africa. For large  $\alpha$  values, the model produces excessive rainfall and large RMSE and bias values.

Not surprisingly, the warm cloud autoconversion threshold  $(l_o)$  has the most significant impact on precipitation amount, since it determines the cloud water content available for precipitation conversion. For Run 1 of Experiment III (Table 5.3), the RMSE (bias) values are excessively high varying from 8.5-11.4 mm d<sup>-1</sup>
(5.3-8.0 mm d<sup>-1</sup>) for Ethiopia, East Africa, and Central Africa, and are larger than the default-run error values (Table 5.4). These errors similarly are high for Experiment IV. For both Experiments III and IV, bias values for 1984 are generally larger than those for 1996. Inspection of the simulated rainfall rate also confirms that the model produced excessive rainfall rate (> 20 mm d<sup>-1</sup>) over most regions for both 1984 and 1996. On the other hand, the threat scores are large for low rainfall thresholds for many of the runs (Table 5.5).

At the other extreme, Run 6 of Experiment III (Tables 5.3, 5.4) produced the lowest RMSE and bias, but significantly underestimated rainfall everywhere except over Ethiopia. The negative bias values, especially for 1996, are indications of this underestimation. This run produced similar rainfall spatial patterns as the modified Anthes-Kuo scheme (Fig. 5.2), with a major center of rainfall maxima over the highlands of Ethiopia and another weak center over Nigeria/Cameroon (not shown). Run 6 of Experiment IV also produced the lowest RMSE and bias in the set (Experiment IV), but overestimated rainfall over much of Ethiopia while underestimating rainfall elsewhere in the model domain. Runs 2 and 3 of Experiment III and IV also produced excessive rainfall rates over most parts of the domain; the magnitudes of the errors, however, are smaller than the errors for the default run. The threat scores generally are large, especially for Central Africa for Runs 2, 3, and 6. Table 5.4 Root mean square (RMS) error and bias (mm d<sup>-1</sup>) for simulations calculated by comparison with Ethiopian station observations and CMAP analysis for regions defined in Fig. 5.10 for Experiments III (E III) and IV (E IV). The RMS error values are averages of 1984 and 1996 peak seasons (July-August). Bias values are shown separately for July-August 1984 and 1996. Except for column 1 (Ethiopia, stations), for which model rainfall rate was interpolated to station locations, the other statistics were computed after interpolating CMAP data onto model grids. Run 5 of Experiment III (highlighted) is selected for further application of RegCM3 over the Horn of Africa because of its best qualities.

	Region														
MIT	Ethiopia			Ethiopia			East			Central			Large		
scheme	(Stations)		(CMAP)			Africa			Africa			Domain			
							(CMAP)			(CMAP)			(CMAP)		
	Ave. Bias		Ave.	Bias		Ave.	Bias		Ave.	Bias		Ave.	Ave. Bias		
	RMS	84	96	RMS	84	96	RMS	84	96	RMS	84	96	RMS	84	96
Run 1 (E III)	11.4	10.2	9.0	10.5	8.6	6.4	8.9	6.8	5.3	8.5	8.1	6.5	4.3	2.0	2.0
Run 1 (E IV)	9.6	6.4	5.8	10.9	5.3	2.8	7.6	2.1	1.3	6.0	4.0	2.5	3.1	0.2	0.0
Run 2 (E III)	6.9	5.4	4.3	6.9	4.6	2.6	5.6	3.4	2.0	6.1	5.9	3.6	2.8	1.0	0.8
Run 2 (E IV)	9.8	7.6	6.3	9.2	5.4	2.5	6.9	2.4	1.1	6.4	3.3	3.4	3.1	0.1	0.0
Run 3 (E III)	5.9	4.1	4.1	5.6	3.3	1.7	4.4	2.2	0.8	5.2	4.5	3.4	2.3	0.5	0.3
Run 3 (E IV)	8.6	6.7	5.9	8.0	4.6	1.6	6.7	2.5	1.4	6.9	6.0	4.3	3.1	0.6	0.4
Run 4 (E III)	4.9	2.9	3.6	4.4	2.1	0.8	3.6	1.3	-0.1	3.8	2.3	1.8	1.8	0.0	-0.1
Run 4 (E IV)	7.4	5.0	4.5	7.1	3.3	1.0	5.5	1.4	0.2	5.4	3.8	2.6	2.6	0.2	0.1
Run 5 (E III)	5.1	3.2	3.0	4.1	1.9	0.1	3.3	1.1	-0.5	3.1	1.7	1.0	1.6	-0.1	-0.2
Run 5 (E IV)	5.7	3.3	4.0	4.8	2.5	0.7	3.8	1.5	0.0	3.9	2.2	2.0	1.9	0.0	-0.1
Run 6 (E III)	4.7	2.9	2.8	4.0	1.6	-0.2	3.4	0.7	-0.8	2.3	-1.8	-1.7	1.7	-0.7	-0.7
Run 6 (E IV)	4.4	3.0	2.2	3.8	2.1	0.3	3.4	1.1	-0.2	2.8	1.5	0.3	1.7	-0.1	-0.3

Table 5.5. Threat scores for July-August simulated rainfall calculated by comparison with Ethiopian raingauge and CMAP analysis for Experiments III (E III) and IV (E IV). The threat scores are computed for regions defined in Fig. 5.10 for rainfall exceeding 2 and 3 mm d<sup>-1</sup> (i.e., threat scores are for rainfall > 2 mm d<sup>-1</sup> and > 3 mm d<sup>-1</sup>, respectively). The values shown are averages of 1984 and 1996 peak seasons (July-August). Except for column 1 (Ethiopia, stations), for which model rainfall rate was interpolated to station locations, the other statistics were computed after interpolating CMAP data onto model grids. Run 5 of Experiment III (highlighted) is selected for further application of RegCM3 over the Horn of Africa because of its best qualities.

	Region									
	Ethiopia		Ethiopia		Ea	ast	Cer	ntral	Large	
MIT	(Stations)		(CMAP)		Africa		Africa		Domain	
scheme	scheme				(CMAP)		(CMAP)		(CMAP)	
				Th	resho	lds (m	m)			
	2	3	2	3	2	3	2	3	2	3
Run 1(E III)	0.94	0.81	0.88	0.78	0.77	0.65	0.89	0.77	0.52	0.57
Run 1(E IV)	0.95	0.85	0.75	0.74	0.68	0.58	0.89	0.90	0.60	0.63
Run 2 (E III)	0.93	0.82	0.87	0.79	0.79	0.70	0.89	0.79	0.66	0.69
Run 2 (E IV)	0.92	0.84	0.79	0.80	0.69	0.62	0.91	0.82	0.61	0.60
Run 3 (E III)	0.93	0.84	0.88	0.79	0.83	0.72	0.90	0.81	0.70	0.72
Run 3 (E IV)	0.94	0.85	0.83	0.78	0.77	0.66	0.90	0.80	0.71	0.72
Run 4 (E III)	0.93	0.84	0.81	0.74	0.73	0.62	0.91	0.85	0.67	0.68
Run 4 (E IV)	0.94	0.84	0.78	0.78	0.73	0.65	0.92	0.84	0.71	0.73
Run 5 (E III)	0.93	0.84	0.81	0.75	0.73	0.63	0.91	0.86	0.67	0.68
Run 5 (E IV)	0.94	0.83	0.80	0.74	0.73	0.65	0.92	0.87	0.66	0.70
Run 6(E III)	0.93	0.85	0.76	0.72	0.63	0.53	0.68	0.41	0.48	0.38
Run 6 (E IV)	0.93	0.83	0.82	0.76	0.72	0.63	0.93	0.83	0.68	0.68

For Runs 4 and 5 of Experiment III, the errors are comparable, but Run 5 performs better than Run 4, having smaller RMSE and bias values for all

domains of error analyses (Table 5.4, Fig. 5.10). Inspection of the simulated precipitation for the two runs also shows that Run 4 significantly underestimated rainfall over eastern Ethiopia in 1996 and missed the sign of the interannual rainfall variation there (not shown). However, no significant advantage emerges when comparing the threat scores for the two runs; in all instances, the threat scores are large (Table 5.5). Run 5 of Experiment III also shows clear advantage over Run 5 of Experiment IV, since it significantly reduces both the RMS and bias errors over the different regions. Overall, the RMSE and bias values for Run 5 of Experiment III are better than the errors for the default runs and the other experiment simulations discussed above.

To highlight further the improvements obtained from Run 5 of Experiment III, Fig. 5.11 presents the spatial patterns of simulated and observed precipitation for 1984 and 1996 and the difference between the two simulated years. The most visible difference between the modified and default MIT simulations (cf. Figs. 5.4 top, 5.11a, b, c) is the reduction of simulated rainfall rates across much of the model domain in the modified simulations, especially over Ethiopia and Central Africa. Although this reduction also occurs over Nigeria, the model still produces excessive rainfall near the model domain boundaries in 1996. Consistent with the observed rainfall (Fig. 5.11d, e), the excessive simulated rainfall (Fig. 5.4 top) over southern Sudan in both 1984 and 1996 now is absent (Fig. 5.11a, b). Instead, the maximum convection is centered over Ethiopia and

eastern portions of the Central African Republic in 1984 and, in agreement with the observed rainfall patterns, the maximum convection over the Central African Republic extends west into southern Chad and eastern Cameroon in 1996.

In the interior areas far from the model boundaries, there is a good degree of similarity between simulated and observed rainfall rates (Fig. 5.11), especially over Ethiopia and Central Africa. The ability of the simulation to identify the interannual variability is strong. The modified MIT simulation clearly reflects the dry (wet) conditions in 1984 (1996) as observed (Fig. 5.11c, f). The simulated difference map (Fig. 5.11c) shows the observed (Fig. 5.11f) excess rainfall in 1996 over central Ethiopia and the Central African Republic/southern Chad, and the negative difference in southwestern Ethiopia (Fig. 5.11f, inset) and the Democratic Republic of the Congo. Substantial improvements have also been made over the Indian Ocean where the modified MIT scheme reproduced the observed positive departure (wetter 1996) well (Figs. 5.7b, 5.9b, 5.11c).

In general, the simulation obtained by combining the effects of  $\alpha$  and  $l_0$  primarily responded to the effects of the warm cloud autoconversion threshold and yielded good results for large values of  $l_0$ . It is clear that the modified MIT scheme (Run 5 of Experiment III) has shown considerable improvement in reproducing the actual rainfall patterns and identifying the observed interannual variations in 1984 and 1996. To test how well the modified MIT scheme performs

under independent forcing, the next section examines the ability of the scheme to simulate the long-term mean state and observed interannual variability.



FIGURE 5.11. Spatial patterns of July-August simulated (top) and observed (bottom) precipitation for 1984 (left), 1996 (middle), and their difference (right). (a) Model precipitation for 1984 using the modified MIT scheme for Run 5 of Experiment IIII (Section 5.4.4, Tables 5.4, 5.5). (b) Same as (a) except for 1996. (c) Difference (1996 minus 1994) in simulated rainfall rates of the modified MIT scheme. (d) Observed precipitation using the CRU data. Inset shows observed station rainfall rates for the northern two-thirds of Ethiopia, with hatching covering non monsoon regions. (e) Same as (d) except for 1996. (f) Observed rainfall difference (1996 minus 1984). Units are mm d<sup>-1</sup>.

### 5.5 Model Climatology and Interannual Variability

This section assesses the ability of the RegCM3 to capture the observed Horn of Africa rainfall amounts and distribution and to reproduce the observed interannual rainfall variability over a long period. This is accomplished by performing multiyear simulations and evaluating how well the model simulates (1) the mean precipitation over the Horn of Africa and (2) the year-to-year rainfall variability over the monsoon regions of Ethiopia. The degree of similarity between modeled and observed interannual precipitation variability is a valuable model diagnostic that measures the sensitivity of the model to a range of synoptic scale atmospheric forcings (e.g., Small et al. 1999).

For this evaluation, the latest RegCM3 release (May 2006) was run using the modified MIT scheme (Run 5 of Experiment III) for 18 years from 1982-1999. The simulation was started in 1982 because the OISST data we used to drive the model are available from December 1981 (Reynolds et al. 2002). The NCEP/NCAR Reanalysis version 1 (Kalnay et al. 1996) was used for the initial and time-dependent atmospheric lateral boundary conditions at 6-hr intervals. The model physical characteristics were discussed in Section 5.4. Simulations were performed only for summer seasons. Thus, for each year, the model was initialized on 25 May and run until 30 September. The first six days of the simulations were considered model spin up and discarded.

Figure 5.12 shows the simulated and observed rainfall climatology for June-September 1982-99. For the observed average rainfall map for the entire Horn of Africa (Fig. 5.12b), CRU data were used over land and CMAP reanalysis data over the ocean. For Ethiopia (Fig. 5.12d), 121 raingauge stations distributed across the entire country were used, although most stations in southern and southeastern Ethiopia do not contribute to the June-September rainfall. The RegCM3 reproduced the mean seasonal rainfall distribution quite well. In addition, the northern and southern limits of the rainfall belt are reasonably represented (Fig. 5.12a, b). Other than the fine details in the model rainfall patterns, there is a striking similarity between simulated (Fig. 5.12a) and observed (Fig. 5.12b) rainfall rates in the interior of the domain far from model boundaries (note the similarity in the 4 mm d<sup>-1</sup> contour). The details in simulated rainfall patterns over Ethiopia closely match the observed raingauge analysis (Fig. 5.12b, d). Note the close similarity in the extended 4 mm d<sup>-1</sup> contour across the southern/eastern highlands in the simulated and station rainfall analyses. This pattern is not apparent in the CRU analysis. The rainfall maximum over western Ethiopia also is well represented, although the model amplifies the magnitude at a few places. Overall, the observed and simulated rainfall climatologies compare well over the Horn of Africa.

However, there are differences in rainfall rates between the modeled and observed patterns, with higher modeled rates in western and southern Ethiopia,



FIGURE 5.12. Spatial patterns of rainfall climatology for June-September for 1982-99. (**a**) Modeled, using the modified MIT scheme for Run 5 of Experiment III (Section 5.4.4, Tables 5.4, 5.5). (**b**) Observed, using CRU over land and CMAP over the ocean. (c) Same as (a) but magnified for Ethiopia. (d) Ethiopian raingauge data for 121 stations covering entire country. Black contours are drawn every 4 mm  $d^{-1}$ .

the Yemen highlands, the Central African Republic, and Nigeria/Cameroon. One reason for the difference between modeled and observed rainfall rates may be related to the CRU data. For example, Afiesimama et al. (2006) suggested that the

CRU climatology may underestimate the observed values over mountainous regions in Africa due to the sparse data density. The major discrepancy between simulated and observed rainfall is over the Indian Ocean, where the CMAP analysis indicates rainfall exceeding 4 mm d<sup>-1</sup> over a large area (Fig. 5.12a, b). The maximum simulated rainfall, on the other hand, is less than 4 mm d<sup>-1</sup> and is limited to a small area in the equatorial Indian Ocean.

The model's ability to capture the observed interannual variability is examined using Ethiopian raingauge data (100 stations across the monsoon regions of Ethiopia) for the 1982-99 period of model integration. First, the modeled, CRU, and CMAP June-September rainfall rates were interpolated using a bilinear interpolation to 100 raingauge locations and spatially averaged for each year to get June-September average rainfall rate time series (1982-99) of modeled, CRU, and CMAP data for Ethiopia. To contrast the performance of the customized MIT convective scheme, the model also was run for the default convective scheme (Grell with Fritsch-Chappell closure, GrFC). Figure 5.13 shows the average Ethiopian rainfall rates computed using model and raingauge stations for 1982-1999.

The default RegCM3 GrFC convective scheme excessively overestimates rainfall (Fig. 5.13). The mean rainfall rate for 1982-99 for the default convective scheme is 9.1 mm d<sup>-1</sup>, which surpasses the observed rainfall rate (6 mm d<sup>-1</sup>) by

more than 50%. Although the modified MIT scheme still produces higher than observed rainfall rates (1982-99 average of 7.6 mm d<sup>-1</sup>), clearly it performs much better than the default convective scheme.



FIGURE 5.13. Interannual variations of Ethiopian June-September average rainfall rates for 1982-99 for raingauge (red), modeled with the modified MIT convective scheme (Run 5 of Experiment III; black), and modeled with the default Grell convective scheme with the Fritsch-Chappell closure (blue). Units are mm d<sup>-1</sup>.

Figure 5.14 illustrates the poor (strong) performance of the default (modified MIT) scheme in capturing the interannual rainfall variability. To facilitate comparison, each time series was centered and scaled by the respective mean and standard deviation. RegCM3's default convective scheme (GrFC) not only excessively overestimates rainfall, but also fails to capture the interannual variability (Fig. 5.14a), with correlation between observed (raingauge) and



FIGURE 5.14. Interannual variations of Ethiopian June-September standardized rainfall rate anomalies ( $\sigma$ ) for 1982-99. (a) Modeled with the default convective scheme (GrFC; blue) and raingauge (red). (b) Raingauge (red), CRU (blue), CMAP (green), and modeled with the modified MIT convective scheme (black).

modeled rainfall being close to zero (-0.05). This poor model performance is especially evident in 1983, 1988, 1996, where the phases of the simulated rainfall anomalies are opposite and their magnitude very large compared to the observed. On the other hand, the modified MIT convective scheme captures the observed rainfall variability well (Fig. 5.14b). The correlation between the raingauge and modified MIT simulated rainfall is +0.66, which is significant at 1% level according to a two-tailed t-test. The correspondence between simulated and CRU (CMAP) rainfall also is substantial (Fig. 5.14b), with correlation values of 0.59 (0.55), both of which are significant at 1% level according to a two-tailed test. Pronounced differences between observed and simulated rainfall occurs only in a few cases, the notable ones being 1983, 1993, and 1998. Thus, the model misidentified the sign of the observed anomalies by either excessively overestimating (e.g., 1983) or significantly underestimating (e.g., 1993, 1998) rainfall for these years. In general, however, simulation results of the modified MIT convective scheme agree well with observations for both rainfall amount (albeit with small positive bias) and interannual variability.

It is interesting to note that while the GrFC scheme gave poor results for Ethiopia, the scheme appears to work substantially better for West Africa (Afiesimama et al. 2006). In fact, Afiesimama et al. (2006) noted that the GrFC mass flux based convective scheme gives a superior reproduction of the observed magnitude and distribution of rainfall over West Africa. Based on 1981-1990

RegCM3 simulations, they found a correlation value of +0.72 between observed and modeled June-September rainfall for the entire West Africa. For the same period, the correlation between modeled and observed rainfall for the Guinea Coast, West Soudano-Sahel, and Central Soudano-Sahel sub-regions of West Africa were +0.51, +0.62, and +0.65, respectively. Although the small number of years used reduce the statistical significance of the above correlation values, there is a clear contrast between the results of Afiesimama et al. (2006) for West Africa and the negligible correlation we found for Ethiopia when the GrFC scheme was used. To compare our result for the modified MIT scheme with the results of Afiesimama et al. (2006), the correlation between modeled and observed rainfall was re-computed for the first 10 years of our simulation, and found that the correlation between Ethiopian raingauge and modeled (with the modified MIT convective scheme) rainfall strengthen further to +0.75 (significant at 2% level according to a two-tailed t-test) for 1982-91. Clearly, the modified MIT scheme is superior in reproducing both the amount and interannual variability of the Ethiopian rainfall.

### 5.6 Summary

The ability of the RegCM3 to reproduce the observed rainfall amounts and distribution for the Horn of Africa was examined. The default MIT convective scheme produced the observed interannual variations, but it excessively overestimated rainfall over much of the model domain. The modified AnthesKuo and Grell schemes perform poorly for the Horn of Africa, both of which fail to capture the observed interannual rainfall variability.

Through exhaustive sensitivity experiments, we reduced the excessive rainfall produced by the MIT scheme. Both qualitative and quantitative evaluations of the model performance have shown that the modified MIT scheme (Run 5 of Experiment III) substantially outperforms the default MIT simulations. The RMSEs for the modified MIT scheme decreased by 46-58% compared to the errors for the default MIT simulation over Ethiopia, East Africa, and Central Africa. The model bias values also have been reduced by 58-83% of the default bias values over those regions. The modified MIT convective scheme also succeeded in capturing the interannual variation over most areas away from the model domain boundaries. Notable among these improvements is the model's success over the Indian Ocean, where the observed wetter conditions in 1996 were successfully simulated.

The evaluation of an 18-year RegCM3 simulation also showed that the modified MIT scheme not only produces the rainfall climatology realistically, but also captures the interannual variability adequately. Thus, the modified MIT scheme will be employed for further application in the current research on the effects of SST variations in the Atlantic and Indian Oceans. The customized model also will be used to assess the impacts of changes in vegetation coverage

on Horn of Africa rainfall. Clearly, the overall improvements made in the model will add to the validity of our study in Chapter 6 that examines the effects of surface boundary conditions on Horn of Africa rainfall and assesses the largescale atmospheric circulation changes associated with prescribed SST forcings over the Indian Ocean.

# CHAPTER 6: EFFECTS OF SST AND VEGETATION COVER ON RAINFALL: OBSERVATIONAL AND MODELING INVESTIGATIONS

# 6.1 Preamble

Major features of the tropical atmospheric circulation, averaged over timescales longer than a month or two, are largely determined by slowly varying SST variations (e.g. Shukla and Paolino 1983; Neelin et al. 1998). Numerous observational and modeling studies have documented the fact that SST variations affect the interannual and decadal fluctuations of seasonal rainfall over different parts of Africa (e.g., Lamb 1978; Folland et al. 1991; Lamb and Peppler 1992; Druyan and Hastenrath 1994; Hastenrath et al. 1995; Semazzi et al. 1996; Ward 1998; Rowell 2003). However, in general, the role of the Atlantic and Indian Oceans in forcing climate anomalies is less well examined and understood than the effects of ENSO-related forcing (Latif et al. 1999).

In this chapter, the effects of SSTs across the Atlantic and Indian Oceans on the Horn of Africa rainfall are explored through observational analysis and modeling studies. Through model experiments, the roles of individual ocean basins in shaping June-September rainfall are examined and documented. In addition, the impact of changes in vegetation cover on rainfall is assessed through model experiments. The observational evidence of SST-rainfall relationships is presented in the next section.

## 6.2 Observational Analysis

To provide an observational background for the modeling experiments in the next section, the effects of SST variations in different ocean basins on Ethiopian rainfall are explored. Specifically, SST anomalies in the Atlantic, Indian, and Pacific Oceans were evaluated in relation to the interannual variability of June-September rainfall averaged over the monsoon regions of Ethiopia (100 stations) for 1970-99. The Ethiopian rainfall data were discussed in detail in Chapter 3. The SST fields were obtained from the NOAA-CIRES Climate Diagnostics Center (Boulder, Colorado; http://www.cdc.noaa.gov/). The data set (the NOAA Extended Reconstructed SST, ERSST) is for a 2 degree latitude by 2 degree longitude global grid constructed using SST data from the most recently available International Comprehensive Ocean-Atmosphere Data Set (ICOADS). The construction involved application of improved statistical methods that allow stable reconstruction using sparse data (Smith and Reynolds 2003). Unlike the monthly OISST data, which are available from 1981 to present (Reynolds et al. 2002; <u>http://www.cdc.noaa.gov/cdc/data.noaa.oisst.v2.html</u>), ERSST data are available from 1854 to present. Because the time span of the ERSST data covers our study period (1970-99), we chose this data to examine the observational link between Ethiopian rainfall and SSTs in different ocean basins.

The ocean basins examined here are the Arabian Sea/northern Indian Ocean (10°-30°N, 40°-80°E), equatorial Indian Ocean (10°S-10°N, 40°-110°E), southern Indian Ocean (10°S-40°S, 50°-110°E), northern tropical Atlantic (10°N-35°N, 22°W-10°W), equatorial Atlantic (10°S-10°N, 22°W-15°E), southern tropical Atlantic (0°-20°S, 22°W-15°E), western equatorial Pacific (10°S-10°N, 130°-150°E), and eastern equatorial Pacific (10°S-10°N, 150°-170°W). Except for the equatorial Pacific, SST variations for the Atlantic and Indian Ocean basins also are investigated in the model experiment section. This research builds on the earlier study of Segele and Lamb (2005) to further identify the temporal evolution of SST-rainfall relationships for Ethiopia. Thus, in addition to providing a background to the modeling study in the next section, this analysis will offer additional evidence supporting the major findings of Segele and Lamb (2005) to that relate global SSTs to Ethiopian Kiremt onset, cessation, and growing length.

The correlation analyses (Fig. 6.1a) show that the eastern equatorial Pacific exhibits the strongest connection with June-September Ethiopian rainfall during the concurrent (reference) monsoon season Y(0). Correlation values for the eastern equatorial Pacific range from -0.58 to -0.68 for June to October, with strongest negative correlation occurring during October. All correlation values for these months are statistically significant at the 1% level. After the end of the monsoon season, especially in Y(0), the maximum correlation magnitude abruptly drops and the relationship between Ethiopian rainfall and eastern and



FIGURE 6.1. (a) Lagged and concurrent correlations between standardized all-Ethiopian June-September rainfall and SST anomalies in the western equatorial Pacific (10°S-10°N, 130°-150°E, solid curve) and eastern equatorial Pacific (10°S-10°N, 150°-170°W, dashed curve). Y(-1) and Y(+1) refer to the years before and after the reference year Y(0). The statistical significance at the 95% and 99% levels according to a two-tailed Student's t-test are shown by thin horizontal lines. (b) Same as (a) except for September all-Ethiopian rainfall anomalies.

western equatorial Pacific SSTs collapses around the boreal spring the following year. This phase change in correlation sign is due to the fact that an anomalous state of the ocean-atmosphere system in the equatorial Pacific Ocean basin tends to decay in boreal spring of the following year in which another state with opposite sign tends to develop (Webster et al. 1998). Such a correlation pattern showing strong biennial variability also is observed for the Indian monsoon rainfall. This is reflected in the striking similarity between Fig. 6.1a and Fig. 2.2, which shows the temporal evolution of the correlation between Indian monsoon rainfall and SST across the equatorial Pacific (Chapter 2). In addition, the correlation patterns in Fig. 6.1 bear a strong resemblance to Nicholls' famous diagram (e.g., Fig. 1 of Nicholls 1988), which depicts the temporal evolution of correlations between Australian Sorghum yield and monthly means of Darwin station-level atmospheric pressure during and before the sorghum growing season. Although different parameters were correlated in Fig 6.1 and Fig. 1 of Nicholls (1988), the timing of the phase change in boreal spring and the persistence of ENSO during July-December for Ethiopia agree well with the corresponding features for Australia. However, the phase change in Y(0) for Ethiopia is not as sharp and abrupt and the persistence of ENSO as long as the corresponding features for Australia.

The seasonal progression of the correlation in Fig. 6.1a further indicates that the eastern equatorial Pacific exhibits a strong predictive signal for JuneSeptember Ethiopian Y(0) rainfall in January of Y(-1), where the correlation reaches -0.59. No statistically significant correlations are evident in Y(+1). On the other hand, the temporal evolution of the correlation between rainfall and SST over the western equatorial Pacific shows opposite correlation patterns that maximize during Y(0), with a maximum correlation value of +0.47 in September. The correlation magnitudes are slightly smaller than those for the eastern equatorial Pacific. In general, the correlation patterns clearly indicate suppressed all-Ethiopian rainfall during El Niño and enhanced rainfall during La Niña, demonstrating a strong teleconnective relationship between the monsoonal Ethiopian rainfall and ENSO.

For individual months, the teleconnection between standardized all-Ethiopian monthly rainfall anomalies and equatorial Pacific SSTs is weak in June, but the relationship strengthens in July, August, and September. The highest correlation between SST and rainfall is attained for all-Ethiopian September rainfall anomalies (Fig. 6.1b). Because the relationship between Pacific SST and Ethiopian monsoon rainfall maximizes towards the end of the season, the resemblance between Fig. 6.1a and 6.1b is very high.

Fig. 6.2a shows the temporal evolution of the correlation between all-Ethiopian June-September rainfall anomalies and SSTs over the Arabian Sea/ northern Indian Ocean and southern Indian Ocean. These ocean basins exhibit



FIGURE 6.2. (a) Same as Fig. 6.1a except for the Arabian Sea/northern Indian Ocean (10°-30°N, 45°-80°E, solid line) and the southern Indian Ocean (10°S-40°S, 50°-110°E, dashed line). (b) Same as (a) except for August all-Ethiopian standardized rainfall anomalies.

the secondmost strong concurrent correlation signals in the reference monsoon season ( $\mathbf{r} \sim -0.58$ ) next to the eastern equatorial Pacific. The lagged correlations for the Arabian Sea/northern Indian Ocean show strong biennial variability. A strong positive correlation between rainfall and Arabian Sea/northern Indian Ocean SSTs occurs in January of Y(0). The correlation decreases through the spring and becomes strongly negative during the monsoon months, reaching statistical significance in August and September. After the end of the reference monsoon season, the lagged correlation magnitude gradually decreases in October-November but abruptly decreases to near zero by the end of Y(0). The correlation remains negative until May of Y(+1), after which it generally increases and remains strongly positive by the end of Y(+1).

The lagged correlation for the Arabian Sea/northern Indian Ocean (Fig. 6.2a) remains negative from January to October of Y(-1) and features a strong negative correlation ( $\mathbf{r}$ ~-0.65) in May of Y(-1). This correlation surpasses the strong negative correlation noted above for eastern equatorial Pacific in Y(-1), and is only slightly less than the magnitude of the concurrent correlation between all-Ethiopian June-September rainfall anomalies and eastern equatorial Pacific SST in August/September ( $\mathbf{r}$ ~-0.67). Clearly, SST over the Arabian Sea/northern Indian Ocean appears to be a strong indicator of the upcoming monsoon season over Ethiopia more than a year before its onset. In fact, this ocean basin possesses a stronger predictive potential than even the eastern Pacific. This is because June-

September (time of maximum concurrent correlation) SST anomalies over the eastern Pacific must be predicted and made available prior to the onset of the rainy season so that the predicted SST values can be used as predictor in an existing empirical model to forecast June-September Ethiopian rainfall. Errors can be introduced in the prediction of June-September SST anomalies, especially considering the ENSO predictability barrier in boreal spring (Webster et al. 1998). Such errors can offset the benefits offered by the underlying strong SST-rainfall association. On the other hand, SST prediction of Arabian SST is not required; i.e., the observed/analyzed Arabian Sea SSTs for May of the previous year are directly used in an existing empirical prediction model to forecast June-September Ethiopian rainfall for the current year. Hence, supported by diagnostic studies and the highly successful wavelet banding prediction technique of Chapter 4, the Arabian Sea/northern Indian Ocean could offer the best information for accurate seasonal rainfall predictions over Ethiopia.

The lagged correlation for the southern Indian Ocean (Fig. 6.2a) largely follows the correlation pattern of its northern counterpart except that (a) the major peaks of the lagged correlations tend to lead those for the Arabian Sea/northern Indian Ocean by 1-2 months, especially in Y(-1) and Y(0), (b) the correlation magnitudes are stronger towards the end of Y(-1), (c) the highest negative correlation is attained towards the end of the reference monsoon season, and (d) the correlations become positive in the early months of Y(+1) and negative after April of that year.

The general features of Fig. 6.2a are reproduced when monthly rainfall anomalies for June, July, and September are correlated separately with Arabian Sea/northern Indian Ocean and southern Indian SSTs, but the most marked difference is observed for August rainfall (Fig. 6.2b). Although not statistically significant, the correlation between all-Ethiopian standardized August rainfall and July and August SSTs over the Arabian Sea/northern Indian Ocean becomes positive. This relationship is not observed for June, July, and September rainfall anomalies, for which the correlations with monthly summer SSTs are strongly negative. Examination of the data shows that Arabian Sea/northern Indian Ocean SST and August all-Ethiopian rainfall anomalies have the same polarity for about 53% of the cases. This is consistent with the overall positive correlation in Fig. 6.2b. Thus, positive July-August SST anomalies over the Arabian Sea can enhance August Ethiopian rainfall. This subject will be examined later in this section. Except for reduced magnitudes, the correlation pattern for southern Indian Ocean SST is similar to Fig. 6.2a.

The effects of SST variations over the equatorial Indian and Atlantic Oceans on June-September all-Ethiopian rainfall anomalies are depicted in the temporal evolution of the correlation signals in Fig 6.3a. Notable features in the



FIGURE 6.3. (a) Same as Fig. 6.1a except for the Equatorial Indian Ocean (10°-10°N, 45°-110°E, solid line) and the equatorial Atlantic (10°S-10°N, 22°W-15°E, dashed line). (b) Same as (a) except for August all-Ethiopian standardized rainfall anomalies.

correlation patterns for the equatorial Indian Ocean are the weak negative correlations during the reference monsoon season, the weak positive correlations in the spring of Y(0), and the strong negative correlations during October-December of Y(0). The strong negative correlations (maximum magnitude of ~-0.64 in November) between equatorial Indian Ocean SSTs for October/November and Ethiopian June-September rainfall suggest windevaporation-monsoon interactions, as described earlier for the TBO (e.g., Chang and Li 2000; Meehl and Arblaster 2002), in which a strong monsoon enhances surface winds that, in turn, lead to increased evaporation and enhanced ocean mixing. This process continuously cools the surface waters and establishes negative SST anomalies over the equatorial Indian Ocean after the end of the monsoon season. The strong negative correlation ( $\mathbf{r}$ ~-0.64) in April of Y(-1) also is noteworthy (Fig. 6.3a). The timing of this correlation is the same as that found for the Arabian Sea/northern Indian Ocean, and thus further underlies the potential for Indian Ocean SST in predicting Ethiopian rainfall several seasons in advance. While SST variations over the equatorial Atlantic do not show a strong correlation with June-September Ethiopian rainfall except in the first semester of Y(-1), they do tend to have the same polarity early in the reference monsoon season (Fig. 6.3a).

As was the case for Arabian Sea/northern Indian Ocean correlation patterns, the lagged correlation between the equatorial Indian Ocean SST and allEthiopian August rainfall becomes less negative/weak positive during the monsoon season (Fig. 6.3b). For the equatorial Atlantic, the correlation patterns changed significantly when the SST-rainfall relationship was examined on monthly basis. In contrast to the weak correlations for June-September rainfall (Fig. 6.3a), the correlations between August Ethiopian rainfall and equatorial Atlantic monthly SSTs were relatively strong negative for the monsoon months, indicating that warmer equatorial Atlantic during (especially) July to September reduces August Ethiopian rainfall (Fig. 6.3b).

Fig. 6.4 presents additional analyses for the tropical Atlantic Ocean. The effects of SST in the northern tropical Atlantic are examined in relation to SST variations in the southern tropical Atlantic using the monthly SST difference between the northern and southern tropical Atlantic (north minus south, N-S). The correlations between June-September all-Ethiopian standardized rainfall and the southern tropical Atlantic (Fig. 6.4a) show a marginal relationship in Y(0) and Y(+1), but statistically significant correlations are achieved early in Y(-1). The correlation for the N-S SST difference follows the same correlation pattern for the southern tropical Atlantic, but with opposite polarity (Fig. 6.4a). The contribution from the northern tropical Atlantic is weak except in summer of Y(-1) and late spring of Y(0), where the magnitudes of the correlations for N-S SST difference slightly increase. In agreement with the correlation for the tropical Atlantic, the SST-rainfall relationship for the tropical Atlantic



FIGURE 6.4. (a) Same as Fig. 6.1a except for the southern tropical Atlantic (20°S-0°, 22°W-15°E, solid line) and SST difference (N minus S; dashed line) between northern tropical Atlantic (N; 10°-35°N, 22°W-10°W) and southern tropical Atlantic (S). (b) Same as (a) except for August all-Ethiopian standardized rainfall anomalies.

significantly increases for August Ethiopian rainfall (Fig. 6.4b). In particular, the correlation between August all-Ethiopian standardized rainfall and southern tropical Atlantic SST is strong and statistically significant at 1% level according to a two-tailed Student's t-test in the summer of Y(0). The correlation for N-S SST difference also changes significantly for August Ethiopian rainfall (Fig. 6.4b), with a change in correlation sign beginning in early summer of Y(0). On the other hand, for both the equatorial Atlantic and the southern tropical Atlantic, the correlations between monthly SSTs and individual monthly rainfall anomalies for June, July, and September are negligible or remain weakly positive/negative during the monsoon months (not shown). The implications of these correlation results are (a) August rainfall contributes significantly to the negative concurrent correlations (especially after July) found for June-September rainfall (Figs. 6.3a, 6.4a), and (b) the equatorial and southern tropical Atlantic SSTs affect Ethiopian rainfall primarily in August. Noting the implication in (a), the negative correlation between August Ethiopian rainfall and equatorial and southern tropical Atlantic SST is consistent with our earlier results in Section 3.4 that showed strong negative correlations between June-September Ethiopian rainfall and equatorial and southern Atlantic SST on seasonal (Fig. 3.29b) and annual (Fig. 3.30b) time-scales. Note that the seasonal and annual modes account for more than 55% of the total June-September Ethiopian rainfall variability.

The monthly correlation patterns discussed above indicate weak correlation values and reversed polarities between monsoon months for the Atlantic and Indian Ocean basins. To examine these relationships in detail, the observed rainfall and SST anomalies in July and August are depicted in Fig. 6.5. Table 6.1 summarizes Fig. 6.5 and gives the number of cases when SST and rainfall anomalies have the same sign. Inspection of Fig. 6.5 and Table 6.1 shows that significant percentages of SST and rainfall anomalies have the same polarity. For the Arabian Sea and the southern Indian Ocean, in more than 53% of years, both SST and rainfall anomalies have the same sign in August. However, for stronger rainfall anomalies (> $|0.25|\sigma$ ), the number of years of the same polarity substantially decreases. For the southern Atlantic and the equatorial Indian Ocean, all-Ethiopian rainfall and SST anomalies have opposite polarities for a large majority of years.

Of particular interest is the year 1984 (Fig. 6.5), during which rainfall and SST anomalies over the Arabian Sea and the equatorial and southern Indian Ocean had the same polarity in July and August. On the other hand, SST anomalies over the southern tropical Atlantic were opposite in sign to all-Ethiopian standardized rainfall anomalies for both months. The magnitudes of the southern tropical Atlantic SST anomalies are larger than the corresponding SST anomalies in the Indian Ocean in July and August. These facts are relevant to the simulation experiments of the next section.



FIGURE 6.5. 1970-99 time series of standardized all-Ethiopian rainfall (green) and SST (red) anomalies for various ocean basins defined in Figs. 6.1-6.4 for (a) July and (b) August.

Table 6.1. Anomaly statistics summarized from Fig. 6.5 showing the number of cases when standardized all-Ethiopian rainfall and ocean basin SST anomalies possess the same polarity. Numbers give years and percentages give the number of cases as fraction of total years (30).

Ocean basin	July	August
Arabian Sea/N. Indian Ocean	14 (47%)	16 (53%)
Equatorial Indian Ocean	13 (43%)	11 (37%)
Southern Indian Ocean	15 (50%)	17 (57%)
Southern Atlantic Ocean	15 (50%)	13 (43%)

In summary, the Arabian Sea/northern Indian Ocean SST pattern exhibits the second strongest (after the eastern equatorial Pacific) concurrent correlation with June-September rainfall, but features the strongest predictive signal more than a year before the rain commences over Ethiopia. The equatorial and southern Indian Ocean basins show moderate to strong negative concurrent correlations with Ethiopian rainfall. While SSTs in the Indian Ocean are negatively correlated with Ethiopian June-September rainfall, the equatorial Atlantic SST shows weak positive (negative) correlations for the first (second) half of summer. For the Arabian Sea and the equatorial Indian Ocean, the correlations between SSTs and August all-Ethiopian rainfall become positive, while for the equatorial and southern Atlantic, the correlations for August rainfall are strongly negative compared to the correlation for June-September rainfall. These correlation analyses highlight the relative importance of the different ocean basins on Ethiopian rainfall. A key finding of the analysis is that the relationships between rainfall and SST are different for seasonal and monthly rainfall anomalies. Moreover, relevant to the simulation study presented next is the fact that Ethiopian rainfall and Indian (Atlantic) Ocean SST anomalies have the same (opposite) polarity in 1984. In the next section, the relative effects of SST variations over the Indian Ocean and the tropical Atlantic are examined through model sensitivity tests.

# 6.3 Effects of the Atlantic and Indian Oceans on Rainfall Variability over the Horn of Africa: Model Sensitivity Studies

The above climatological assessment shows that SSTs over the Atlantic and Indian Ocean affect Ethiopian rainfall to a varying degree. To understand the large-scale atmospheric response to SST forcings over the Atlantic and Indian Oceans, several simple sensitivity studies involving SST variations over different ocean basins were performed using the recent RegCM3 release (May 2006). As indicated in Chapter 5, the changes in the new version primarily enhance the functionality of the model and do not affect the model's dynamical core and physics. In addition, the long-term simulations performed in Section 5.5 using the latest release have shown that RegCM3 realistically reproduces the observed rainfall variability over the Horn of Africa. A full description of RegCM3 was given in Chapter 5.

#### 6.3.1 Experimental Design and Data Sets

Several experiments were performed to examine the effects of SST variations in the Mediterranean Sea, the Atlantic, and the Indian Ocean. The experiments involve modifying SST anomalies over a specific ocean basin while prescribing seasonally varying climatological SSTs elsewhere in the model domain. This strategy was implemented in several atmospheric GCM studies to identify the dynamical atmospheric response to SST forcing and examine regional SSTrainfall relationships for different parts of Africa including West Africa (e.g., Folland et al. 1991; Rowell 2003) and central, eastern, and southern Africa (e.g., Goddard and Graham 1999; Latif et al. 1999). However, unlike GCMs for which only initial conditions and SST forcing are needed, the RegCM3 requires additional time-dependent atmospheric boundary conditions. These atmospheric initial and boundary conditions can be climatological data (e.g., 4 times daily surface pressure, and surface to upper level wind, temperature, and moisture) or actual time-dependent reanalysis fields.

Climatological atmospheric boundary conditions would probably be more appropriate for these SST experiments, but 6-hourly climatological data are not readily available for RegCM3 use. Because of computational resource and time limitation, we were not able to develop the required climatological atmospheric data. Instead, we chose to use the 6-hr NCEP/NCAR Reanalysis (Kalnay et al. 1995) atmospheric initial and boundary data for two extreme years that were
used in validating the RegCM3; i.e., 1984 and 1996. For SST specification, both monthly climatologies and actual monthly OISST (Reynolds et al. 2002) data were used. Monthly SST climatologies were obtained by averaging the eighteen monthly values at each grid point (1-degree latitude/longitude) for 1982-1999.

Understanding the dynamical atmospheric response to SST forcing for different ocean basins for 1984 is of substantial scientific interest because it was one of the driest years for much of sub-Saharan Africa. On the negative side, the results of SST experiments that are initialized and constrained by large-scale circulation patterns of a given year may be influenced by the atmospheric characteristics of that year. This caveat undermines the generality of the SST sensitivity experiments. To assess the impacts of atmospheric initial and boundary conditions, we performed identical SST experiments for some of the simulations using 1996 atmospheric data. Noting the substantial differences between the large-scale flow in 1984 and 1996 for Ethiopia (Segele and Lamb 2005), a significant commonality between model simulations differing only by initial and boundary atmospheric data for 1984 and 1996 is a clear indication of the model's ability to isolate a prescribed SST forcing. As will be shown later, substantial similarities were found between experiments that differ only by atmospheric initial and boundary conditions.

To examine the effects of SST variations across the Mediterranean Sea, the Atlantic, and Indian Ocean, several experiments were carried out for the domain shown in Fig. 6.6. For SST sensitivity investigation, a number of ocean basins in the Atlantic and Indian Oceans were selected (1) based on their importance (from results of Chapter 3) to Horn of Africa rainfall (e.g., the Arabian Sea and southern Indian Ocean), (2) to contrast SST effects within an ocean sector (e.g., the Atlantic sector is defined to include the equatorial Atlantic), and (3) based on results of previous studies (e.g., interhemispheric SST difference in northern and southern Atlantic; to be discussed later). Thus, the Indian Ocean was partitioned into 4 subdivisions-the Arabian Sea/northern Indian Ocean (ArbS; 10°-30°N, 40°-80°E), equatorial Indian Ocean (EqIO; 10°S-10°N, 40°-110°E), southern Indian Ocean (SIO; 10°S-40°S, 50°-110°E), and the entire Indian Ocean (IO, 40°S-30°N, 40°-110°E). Similarly, the Atlantic was divided into 5 basins-the equatorial Atlantic (EqAT; 10°S-10°N, 22°W-15°E), southern Atlantic (SAT; 10°S-40°S, 22°W-20°E), Atlantic sector south of 10°N (AT; 10°N-40°S, 22°W-20°E), northern tropical Atlantic (NtAT; 10°-35°N, 10°-22°W), and southern tropical Atlantic (StAT; 0°-20°S, 22°W-15°E). The MDTR region was defined to cover the entire Mediterranean Sea and the Black Sea (MDTR; 30°-46°N,5°W-42°E). All of the aforementioned ocean regions are shown in Fig. 6.6.

For the control experiments, climatological SSTs were prescribed for the entire domain (Fig. 6.6), but the simulations were performed using the NCEP-



FIGURE 6.6. Complete model domain showing the individual ocean basin areas for the different experiments defined in Table 6.2 and discussed in the text.

NCEP Reanalysis data for atmospheric initial and boundary conditions for 1984 and 1996. These control simulations are identified by the last two digits of the year for the atmospheric initial and boundary data; i.e., CTRL84 and CTRL96. In addition, two other simulations were performed using the actual OISST and NCAR/NCEP Reanalysis data for 1984 and 1996 for the entire domain. These simulations are referred to as ACTL84 and ACTL96. Each control (forced by climatological SST) and actual (forced by observed OISST) simulation is used to compare simulation results that employ identical atmospheric initial and boundary data. These experiments are summarized in Table 6.2.

Experiment	Description
CTRL84	Seasonally varying climatological SST over entire domain; Reanalysis for 1984
CTRL96	Same as above but Reanalysis for 1996
ACTL84	Observed OISST for 1984; Reanalysis for 1984
ACTL96	Observed OISST for 1996; Reanalysis for 1996
ATw84	Seasonally varying climatological SST over entire domain except over the Atlantic where SSTs are increased by 1K; Reanalysis for 1984
IOw84	Same as above except for the Indian Ocean sector
ArbSw84	Same as above except for the Arabian Ocean/northern Indian Ocean
EqATw84	Same as above except for the equatorial Atlantic
EqIOw84	Same as above except for the equatorial Indian
EqIOc84	Seasonally varying climatological SST over entire domain except over the equatorial Indian Ocean where SSTs are decreased by 1K; Reanalysis for 1984
EqIOw96	Seasonally varying climatological SST over entire domain except over the equatorial Indian where SSTs are increased by 1K; Reanalysis for 1996
EWgrdIO84	Seasonally varying climatological SST over entire domain except over equatorial Indian Ocean where zonally eastward decreasing SST anomalies with 2K amplitude warm (cool) the western (eastern) equatorial Indian Ocean; Reanalysis for 1984
EWgrdIO96	Same as above but Reanalysis for 1996
MDTRw84	Seasonally varying climatological SST over entire domain except over the Mediterranean Sea where SSTs are increased by 1K; Reanalysis for 1984
NwScAT84	Seasonally varying climatological SST over entire domain except 1K warming over northern tropical Atlantic and 1K cooling in the southerr tropical Atlantic; Reanalysis for 1984
NcSwAT84	Seasonally varying climatological SST over entire domain except 1K cooling over northern tropical Atlantic and 1K warming in the southern tropical Atlantic; Reanalysis for 1984
SATw84	Seasonally varying climatological SST over entire domain except over southern Atlantic where SSTs are increased by 1K; Reanalysis for 1984
SIOw84	Seasonally varying climatological SST over entire domain except over southern Indian Ocean where SSTs are increased by 1K; Reanalysis for 1984

Table 6.2. List of the RegCM3 experiments discussed in the text.

For warm SST sensitivity experiments, SSTs were increased by 1K in the ArbS, EqIO, SIO, IO, MDTR, EqAT, SAT, and AT sectors separately while prescribing the 18-year average SST everywhere else in the model domain for each experiment. The simulations with the above prescribed SST and using atmospheric initial and boundary conditions for 1984 are identified by their ocean basin names, the SST anomaly type (w), and the last two digits of the year, i.e., ArbSw84, EqIOw84, SIOw84, IOw84, MDTRw84, EqATw84, SATw84, and ATw84 (Fig. 6.6, Table 6.2). Each of the above experiment is compared with the CTRL84 simulation to assess the changes arising from the prescribed SST forcing, the only difference between the CTRL84 and the above individual sensitivity experiments being the warm SST anomalies in the warm simulations.

In the EqIO sector, two additional simulations corresponding to two distinct SST specifications were performed. (1) To examine the effects of warm (cold) SST anomalies over the western (eastern) EqIO, westward linearly increasing SST anomalies were added to the climatological SST over the EqIO while maintaining the 18-year average SSTs elsewhere in the model domain. This SST specification crudely follows a reversed SST gradient in the Indian Ocean associated with the so called "Indian Ocean Dipole", as depicted in Fig. 2 of Webster et al. (1999). The climatological SSTs over the western Indian Ocean (10°S-10°N, 45°-70°E) were increased by a maximum of +2K off the coast of eastern Africa and then linearly decreased eastward to zero at 70°E. Over the eastern Indian Ocean (10°S-

10°N, 70°-110°E), the climatological SSTs were linearly further reduced eastwards with a maximum negative anomaly of -2K applied at the eastern extreme (110°E). This east (E) to west (W) increasing zonal SST gradient (grd) in the EqIO (IO), with initial and boundary atmospheric conditions for 1984, is referred to as EWgrdIO84. (2) To contrast the large-scale atmospheric response to positive SST anomaly forcing and assess the model rainfall response, the EqIOw84 simulation was repeated with a cold (c) SST anomaly of -1K added to the 18-year average SST over the same ocean basin (EqIOc84). Because the only difference between the EqIOc84 and EqIOw84 simulations is the specification of equal but opposite SST anomalies in the EqIO, comparison of the two simulation results would show the strength of the forcing and the degree of linearity in the atmosphere response to identical but opposite SST anomaly forcings.

Over the tropical Atlantic, interhemispheric meridional SST gradient is observed in the course of the average annual cycle, with maximum contrasts during March-April (e.g., Curtis and Hastenrath 1995). Of particular interest is Lamb and Peppler's (1992) empirical documentation of the atmospheric-oceanic conditions accompanying sub-Saharan drought. They found that in three of the four severe sub-Saharan drought years since 1940 (1972, 1977, and 1984), a distinctive basinwide SST anomaly pattern prevailed in the tropical Atlantic Ocean, with positive departures (from a 60-year average) to the south of ~10N and negative departures to the north. The interhemispheric SST difference for July-September was pronounced in 1984 (Fig. 2 of Lamb and Peppler 1992). To examine the effects of such interhemispheric SST difference on Horn of Africa rainfall, the 1982-99 average SST was cooled (c) by -1K in the NtAT (N) and warmed (w) by +1K in the StAT (S) while maintaining the 1982-99 average SST in the remaining areas of the domain (Fig. 6.6). This experiment with the above SST specification in the Atlantic (AT) was performed using initial and boundary atmospheric conditions for 1984, and is referred to as NcSwAT84. To assess further the strength of the atmosphere response to the above SST specification, the NcSwAT84 was repeated by reversing the sign of the SST anomalies in the northern and southern tropical Atlantic, i.e., the 1982-99 average SST was increased (decreased) by +1K (-1K) in the NtAT (StAT). This experiment is referred to as NwScAT84.

In addition, to test the sensitivity of model solutions to atmospheric boundary conditions, the EqIOw84 and EWgrdIO84 experiments were repeated using 6-hr NCEP/NCAR Reanalysis boundary conditions for 1996. These simulations are referred to as EqIOw96 and EWgrdIO96. As indicated earlier, the simulation with 1996 atmospheric data will be compared with the CTRL96 and ACTL96 simulations.

Thus, in addition to the basic SST experiments that investigate the impacts of SST forcing in several ocean basins, a number of other model simulations were

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performed to assess the sensitivity of the SST forcing and the validity of the results. The EqIOw84, EwIOc84, NwScAT84, and NcSwAT84 experiments contrast the effects of warmer and colder SST forcing and enable us to examine the degree of linearity and the strength of the model rainfall response to prescribed SST anomalies in the Indian Ocean (EqIOw84, EwIOc84) and the Atlantic (NwScAT84, NcSwAT84). On the other hand, comparisons of the EqIOw84 and EqIOw96 simulations and the EWgrdO84 and EWgrdIO96 experiments would show the impacts of initial and boundary conditions for different SST forcings (i.e., uniform +1K warming in the EqIO and linearly eastward decreasing SST anomaly of +2K amplitude in the western EqIO and -2K amplitude in the eastern EqIO). Thus, repeating the basic SST sensitivity experiments using different initial and boundary conditions or forcing the experiments with the opposite SST anomalies hopefully increases the reliability of the model sensitivity results. Comparisons are made by computing differences from the appropriate control simulations. Such difference fields are expected to reveal the effects of the prescribed SST forcing on local/regional rainfall.

Table 6.2 summarizes all experiments described above. To allow a smooth transition between the 1982-99 average SST field and the modified field within each ocean basin, a linear interpolation was performed by increasing/decreasing the 1982-99 average SST to the modified SST values over 4 grid points at the edge of each ocean basin. For each of these experiments, the model was run from 25

May to 30 September at a horizontal resolution of 90 km and a time step of 3 minutes. Also, because of its success, the modified MIT scheme (Run 5 of Experiment III; Chapter 5) is used for all simulations. First, results of the control simulation for 1984 atmospheric initial and boundary conditions, for which the basic SST experiments were performed, are presented in the next section.

## 6.3.2 Control Simulation for 1984 Atmospheric Initial and Boundary Conditions

The CTRL84 simulated rainfall was used as a reference to assess changes in simulated rainfall associated with SST forcing over different ocean basins. The CTRL84 simulation produced a realistic rainfall distribution for June-September (Fig. 6.7a) that compared well with the simulated and observed rainfall climatology for 1982-99 (see Fig. 5.12). However, the main rainfall center shifted to the east by about 2°. The difference between the ACTL84 and CTRL84 runs should primarily reflect the effects of SST differences across the model domain as the two simulations differ only by lower boundary (SST) conditions. The CTRL84 June- September model rainfall significantly exceeded the ACTL84 rainfall over western, southern, and eastern Ethiopia and over northern Eritrea, as indicated by the difference (ACTL84 minus CTRL84) map in Fig. 6.7b. However, the overall seasonal simulated rainfall patterns show differences in the magnitudes of departures for individual months (Fig. 6.7c, d). In July, the CTRL84 simulated rainfall was wetter than the ACTL84 run especially for Ethiopia (Fig. 6.7c). In



FIGURE 6.7. Spatial patterns of simulated precipitation fields. (a) Simulated precipitation for the control run (CTRL84) for June-September (contours every 4 mm d<sup>-1</sup>). (b) Difference between the actual and control (ACTL84 minus CTRL84) simulated precipitation for June-September. (c) Same as (b) except for July. (d) Same as (b) except for August. Units are mm d<sup>-1</sup>.

contrast, for August, ACTL84 minus CTRL84 indicates excess rainfall primarily along the western borders of Ethiopia and Eritrea and along the highlands of Somalia, and drier conditions over central and southwestern Ethiopia in August (Fig. 6.7d).

The anomalous (ACTL84 minus CTRL84) seasonal SST forcing is shown in Fig. 6.8. A strong similarity exists between the June-September 1984 SST anomalies over the tropical Atlantic shown in Fig. 6.8 (based on 1982-99 SST average) and the July-September 1984 SST anomalies displayed in Fig. 2 of Lamb and Peppler (1992) computed from a 60-year average. Compared to the CTRL84, the ACTL84 simulation is forced by colder SSTs over the Indian Ocean west of 80°E and north of 20°S, the Mediterranean Sea, and northern tropical Atlantic, and by warmer SSTs over the tropical Atlantic south of 20°N and southeastern Indian Ocean. The outcome of this SST distribution is drier (compared to the CTRL84 simulated values) June-September rainfall over most of Ethiopia, Eritrea, and coastal areas of Somalia. However, the effects of individual ocean basins cannot be inferred from these two first-order simulations.



FIGURE 6.8. Spatial patterns of SST anomalies (K) for June-September 1984. Anomalies are departure from 1982-1999 climatology.

Although there are some differences in SST anomalies for July and August 1984 (Fig. 6.9) over the northern Arabian Sea, southeastern Indian Ocean, and



FIGURE 6.9. (a) Same as Fig. 6.8 except for July 1984. (b) Same as (a) except for August 1984.

western Mediterranean, the monthly SST anomaly distributions for these months resemble closely the seasonal SST anomalies in Fig. 6.8. Inspection of the SST anomaly fields shows that July 1984 SSTs are colder than August 1984 SSTs over the northern Arabian Sea and western Indian Ocean, and warmer than August 1984 SSTs over the southeastern Indian Ocean and western Mediterranean Sea (Fig. 6.9a, b). Furthermore, the southern tropical Atlantic warming appears to expand and strengthen in August 1984. It is unclear how these SST differences can explain the difference between July and August simulated rainfall in north-central Ethiopia (Fig. 6.7c, d). To investigate the likely effects of individual ocean basins, several sensitivity experiments were performed to isolate the effects of individual oceans by specifying SSTs over selected regions. Separate results are presented for the Indian Ocean and for the Atlantic and the Mediterranean Sea. The next section discusses the simulation results for the Indian Ocean sector.

## 6.3.3 Impacts of SSTs over the Indian Ocean for 1984 Atmospheric Initial and Boundary Conditions

The effects of SST variation over the Indian Ocean are seen readily in Fig. 6.10, which depicts rainfall departures from the CTRL84 of simulations forced by various regional SST anomalies in the Indian Ocean sector. The areas of the Indian Ocean considered are the ArbS, EqIO, SIO, and IO (Fig. 6.6). The experiments were described in Section 6.3.1 and summarized in Table 6.2. In general, warming/cooling over different Indian Ocean basins tend to induce wetter (Fig. 6.10a, b, c, e, f)/drier (Fig. 6.10d) seasonal rainfall over much of the Horn of Africa. However, there are significant spatial and temporal variations in the rainfall departure fields for all simulations.



FIGURE 6.10. Plots of June-September rainfall departures (mm d<sup>-1</sup>) from the control values for simulations forced by SST warming/cooling in different areas of the Indian Ocean basin. Fig. 6.6 and Table 6.2 provide the details of the experiments. (a) ArbSw84 values minus CTRL84 values. (b) Same as (a) except for EWgrdIO84 run. (c) Same as (a) except for EqIOw84 run. (d) Same as (a) except for EqIOc84 run. (e) Same as (a) except for SIOw84 run. (f) Same as (a) except IOw84 run.

The ArbSw84 run, forced by +1K warming in the ArbS basin (Fig. 6.6, Table 6.2), simulated wetter conditions through much of Ethiopia, Djibouti, and Eritrea (Fig. 6.10a). Of all the simulations, the ArbSw84 experiment caused the largest widespread June-September wet conditions in the monsoon regions of the Horn of Africa (Fig. 6.7a). The largest positive effect on Horn of Africa rainfall from Arabian Sea warming occurred in August, when much of Ethiopia experienced wetter conditions compared to August CTRL84 rainfall. However, dry conditions persisted over west-central Ethiopia, especially in July and September (not shown). Because the difference between the ArbSw84 and CTRL84 experiments is the +1K warming of the ArbS, the simulated rainfall difference suggests that the observed 1984 negative SST anomaly in the ArbS sector (Fig. 6.8) might have contributed to the observed dryness in Ethiopia, assuming (as will be shown later) that the opposite experiment with negative anomalous SST forcing in the ArbS would give the reverse of the ArbSw84 simulation result.

The EWgrdIO84 experiment assesses the effects of a westward increasing SST anomaly over the EqIO (Fig. 6.6, Table 6.2). This simulation strongly affects the equatorial regions of Ethiopia, Somalia, and Kenya (Fig. 6.10b), which have seasonal rainfall peaks in April and October. The wettest anomalies of this experiment are off the coasts of Kenya and Somalia, where warmer SST anomalies were specified. Inspection of the EWgrdIO84 simulated monthly

rainfall reveals wetter conditions in September and drier conditions in July/August especially over central and western Ethiopia (not shown). In particular, consistent with the observed effects of warm equatorial waters off the coast of east Africa and cool waters farther east in the equatorial Indian Ocean, the wet anomalies are stronger by the end of the monsoon season/the beginning of the short rainy seasons in southern Ethiopia and Kenya. Note that, climatologically, the east-west SST anomaly gradient maximizes in October/November (e.g., Hastenrath et al. 1993; Webster et al. 1999), at the peak of the second short rainy season in Ethiopia and Kenya. Interestingly, a 2K amplitude increase (decrease) of climatological SST over the western (eastern) Indian Ocean has produced only a weak June-September SST gradient between eastern and western waters.

The EqIOw84 experiment examines the effects of warm SST anomalies in the EqIO (Fig. 6.6, Table 6.2). The wet anomalies produced by the EqIOw84 simulation are strongest over extreme western Ethiopia (Fig. 6.10c) compared to the other simulations involving SST specifications over the Indian Ocean sector. Simultaneously, pockets of west-central Ethiopia experience drier conditions in all months, but especially in September. Examination of the daily simulation data indicates prolonged dry spells in west-central Ethiopia beginning in late August. These dry spells extended into early to mid-September. The main differences between the ArbSw84 and EqIOw84 simulations are the time and location of the

wettest rainfall. For the EqIOw84 simulation, the wettest period occurs in July and the highest rainfall tends to be in western Ethiopia. On the other hand, the ArbSw84 simulation produces abundant rainfall over southwestern, central, and northeastern Ethiopia in August. However, the overall June-September rainfall departures for the EqIOw84 and the ArbSw84 simulations bear strong similarity, both featuring positive rainfall departures over eastern and extreme western Ethiopia and negative departures in west-central Ethiopia.

The EqIOc84 experiment investigates the effects of colder SST anomalies over the EqIO (Fig. 6.6, Table 6.2). This SST specification is opposite to the EqIOw84 experiment. Hence, the EqIOc84 run would show the sensitivity of the model to prescribed SST anomalies. In contrast to the EqIOw84 run, the EqIOc84 simulation reduced rainfall over much of Ethiopia, especially along the Main Rift Valley and eastern Ethiopia, and produced wetter conditions in northern Eritrea (Fig. 6.10d). The absence of the large positive departure over western Ethiopia in the EqIOc84 experiment is a good indication of the difference between the EqIOc84 and EqIOw84 simulations. However, the negative departure for the EqIOc84 run is limited to parts of southwestern Ethiopia. The large negative departure southeast of Lake Tana (Fig. 6.10c) is appreciably weakened, reverses sign, or moves into the Rift Valley regions for the EqIOc84 experiment (Fig. 6.10d). Although the simulated rainfall departures (from CTRL84) for the EqIOc84 run are not opposite to those found for the EqIOw84 experiment (Fig.

6.10c), most areas exhibit negative rainfall departures for the EqIOc84 experiment than for the EqIOw84 simulation. Clearly, the reversed (cold) SST anomaly forcing significantly reduced rainfall across much of the Horn of Africa.

The SIOw84 experiment examines the response to warm SIO (Fig. 6.6, Table 6.2). The simulated rainfall departure (SIOw84 minus CTRL84) pattern is similar to the EqIOw84 run except that the magnitude of departure is smaller over western Ethiopia (Fig. 6.10e). However, there are significant rainfall differences between the SIOw84 and EqIOw84 simulations over Eritrea and the Arabian Peninsula, where the SIOw84 run produced drier conditions compared to the control run.

Finally, the IOw84 simulation assesses the response to a hypothetical all-Indian Ocean warming (Fig. 6.6, Table 6.2). The simulation result indicates that warming of the entire Indian Ocean has the effect of enhancing (reducing) rainfall over the southern (northern) half of the monsoon regions in the Horn of Africa (Fig. 6.10f). The dryness in the northern half is particularly acute in July and August (not shown). This pattern is reversed in June and especially September, yielding overall wet conditions in Eritrea (Fig. 6.10f). Although the SST scenario for the IOw84 simulation is nearly the geographical combination of the ArbSw84, EqIOw84, and SIOw84 simulations, the outcome of the IOw84 simulation in July and August is different from these three runs. Additional experiments may be needed to understand the causes of the disparity between the IOw84 and the ArbSw84, EqIOw84, and SIOw84 experiments.

The overall effects of warm SSTs over the Indian Ocean sector are assessed using simulated rainfall averaged over the 100 Ethiopian station locations (Fig. 3.3a) for individual months of June-September (Fig. 6.11). The figure highlights the month-to-month variations of the different simulations. To examine the relative effects of SST forcing in different areas of the Indian Ocean basin, the simulated rainfall from the sensitivity experiments are compared to the CTRL84 simulated rainfall.

The different runs show strong sensitivity response in different months (Fig. 6.11). The ArbSw84 run has the strongest effect in August during which abundant rainfall was simulated across much of Ethiopia. This forcing is opposite to the observed colder than climatology 1984 SST anomaly (Fig. 6.8). The EWgrdIO84 simulation show increased rainfall in September (especially over southern regions) and drier conditions in July (especially over central and western Ethiopia). The effect of warmer waters over the equatorial Indian Ocean is strongly felt in July in which widespread positive anomalies cover most places, especially western portions of Ethiopia. This positive SST anomaly also is opposite to the observed negative anomaly in 1984 (Fig.6.8), although the magnitude of the observed 1984 SST anomaly in the EqIO was less than the

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FIGURE 6.11. All-Ethiopian June-September observed and simulated rainfall (mm d<sup>-1</sup>) for SST specifications over different regions of the Indian Ocean sector given In Fig. 6.6. and Table 6.2. The region average simulated rainfall is obtained by averaging model grid rainfall for the closest four grids surrounding each of the 100 Ethiopian station locations and averaging the interpolated values for individual months. The results of applying a bilinear interpolation method were quite similar to those results obtained by averaging the nearest four grid points surrounding a station.

anomaly in the ArbS. In contrast, the EqIOc84 simulation, which parallels the observed negative anomaly in 1984 over the EqIO (Fig. 6.8), produced the lowest rainfall in July. These results indicate (a) strong model sensitivity to SST forcing, (b) equal but opposite SST anomaly forcings tend to produce contrasting but not symmetric rainfall departures, and (c) SSTs in the Indian Ocean sector also contributed to the observed rainfall deficiency in 1984. Warm SSTs over the southern Indian Ocean significantly enhance rainfall in August, but when the

entire Indian Ocean is warmer than climatology, a north-south dry-wet rainfall pattern develops in July and August. Comparing the ArbSw84, IOw84, and EWgrdIO84 simulations, it can be noted that warm SSTs over the Arabian Sea/off the coast of eastern Africa favor wetter conditions over Ethiopia during the start and end of the monsoon in the Horn of Africa.

Using the conclusions in (a) and (b) above and noting that there is strong similarity in the June-September rainfall departure maps for EqIOw84 and ArbSw84 experiments, comparison of Fig. 6.5 for 1984 and Fig. 6.11 indicates that model results are qualitatively consistent with the observed SST and all-Ethiopian rainfall anomaly relationship. For example, in July 1984, all-Ethiopian rainfall anomaly and SST anomalies over the Arabian Sea, equatorial Indian Ocean, and southern Indian Ocean were negative. Compared to the CTRL84 simulated rainfall, positive SST anomalies over those ocean basins also yielded wetter rainfall. Leaving aside the fundamental computational difference between the observed standardized rainfall anomalies and modeled averaged rainfall, the model results clearly maintained the sign relationship, i.e., warm SSTs over the ArbS, EqIO, and SIO enhanced rainfall over Ethiopia. The same description holds for August SST-rainfall relationship, especially for the ArbS and EqIO.

Our above findings on the effects of Indian Ocean SSTs on the Horn of Africa rainfall are consistent with previous findings on rainfall-SST relationships for

Africa (Section 2.3.6). For example, Latif et al. (1999) indicate that warmer Indian Ocean produces enhanced precipitation over eastern equatorial Africa. Goddard and Graham (1999) suggest that the central-eastern/southern Africa precipitation anomalies partially arise from changes in convective heating over the Indian Ocean driven largely by SST changes. The model sensitivity studies in this section reveal that the effects of SSTs over the ArbS and EqIO are strongest during the peak of the summer season in July and August. Although this model sensitivity study does not explicitly show the effects of SSTs on the onset and cessation of Ethiopian rainfall season, the wetter conditions especially in September for the ArbSw84, EqIOw84, and EWgrdIO84 simulations indicate that warm SSTs over the western Indian Ocean likely favor delayed cessation of the monsoon in Ethiopia. This is consistent with the results of Segele and Lamb (2005), who found positive correlations between the cessation of the monsoon over eastern and northeastern Ethiopia and SSTs over the western Indian Ocean.

# 6.3.4 Impacts of SSTs over the Atlantic for 1984 Atmospheric Initial and Boundary Conditions

The simulated effects of SST variations over the Atlantic Ocean sector and the Mediterranean Sea on rainfall over the Horn of Africa are shown in Fig. 6.12. The areas of the Atlantic examined are the EqAT, SAT, AT, NtAT, and StAT (Fig. 6.6). The experiments were described in Section 6.3.1 and summarized in Table 6.2. Although the simulations, in general, were designed to assess the effects of hypothetical basinwide warming in the Atlantic and the Mediterranean Sea, the SST specification in the NcSwAT84 experiment was patterned following the observed colder (warmer) 1984 SST in the northern (southern) tropical Atlantic (present Fig. 6.8; Fig. 2 of Lamb and Peppler 1992). The strength of the atmosphere response to this SST specification was further examined using a reversed SST gradient in the tropical Atlantic, with warming (cooling) in the northern (southern) tropical Atlantic (NwScAT84). The observational evidence of the SST-rainfall relationship for the Atlantic was presented in Section 6.1.

An outstanding feature of the simulations is that warming over the Atlantic and the Mediterranean Sea primarily affects rainfall over northwestern Ethiopia and southern Eritrea (Fig. 6.12a, b, e, f), where significant positive departures from the control run cover large areas. The EqATw84 (Fig. 6.12a) and SATw84 (Fig. 6.12b) runs reduce rainfall over central and eastern Ethiopia, and increase it over northern Ethiopia and southern Eritrea, especially in July and September (not shown). The primary difference between these two simulations is that the SATw84 run produces drier July than the EqATw84 run (e.g., Fig. 6.14).

Warming of the Atlantic Ocean sector south of 10°N (ATw84) generally enhances (reduces) rainfall in the northern (southern) regions of the domain (Fig. 6.12c). The effect of this forcing is minimal in June but increases in July, August, and September (not shown). The simulated monthly rainfall distribution (not



FIGURE 6.12. Plots of June-September rainfall departures (mm d<sup>-1</sup>) from the control run for simulations forced by SST warming/cooling in the Atlantic and Mediterranean Sea. Fig. 6.6 and Table 6.2 provide the details of the experiments. (a) EqATw84 values minus CTRL84 values. (b) Same as (a) except for SATw84 run. (c) Same as (a) except for ATw84 run. (d) Same as (a) except for MDTRw84 run. (e) Same as (a) except for NwScAT84 run. (f) Same as (a) except for NcSwAT84 run.

shown) further indicates drier conditions in July but wetter conditions in August over most regions in Ethiopia and Eritrea. In September, much of Eritrea and northern Ethiopia received excessive rainfall while central Ethiopia had significant deficiencies. Thus, the seasonal rainfall departure distribution (Fig. 6.12c) in Eritrea (central Ethiopia) primarily reflects the excessive (deficient) simulated rainfall in August-September (July). This distribution also is reflected for the SATw84 simulation. In addition, the difference between the ATw84 and SATw84 simulated rainfall spatial distribution is very small (Fig. 6.12b, c), indicating a weak influence of equatorial Atlantic warming (note the weak magnitude of rainfall departures in Fig. 6.12a).

The MDTRw84 experiment, forced by +1K SST anomalies in the Mediterranean Sea and Black Sea (Fig. 6.6, Table 6.2), produced positive rainfall departures in Eritrea and northern, central, and southwestern Ethiopia (Fig. 6.12d). Unlike the ATw84 run, the MDTRw84 simulation affects the Horn of Africa rainfall distribution beginning in June. The strongest seasonal effect is on northwestern Ethiopia and western Eritrea, but abundant rainfall covers central and southwestern Ethiopia in June and August, and western and northwestern Ethiopia in June and August, and western of Africa June-September rainfall in the MDTRw84 simulation is consistent with a GCM simulation result of Rowell (2003), who showed that years with warmer (cooler)

than average July-September SSTs in the Mediterranean are often wetter (drier) over the Sahel.

The NwScAT84 and NcSWAT84 simulations examine the effects of the north-south Atlantic SST gradient on the Horn of Africa rainfall (Fig. 6.6, Table 6.2). Although the magnitudes of the north-south (area average) SST differences in the Atlantic Ocean resulting from the specification of ±1K anomalies magnify the observed gradients, they are not unrealistic. For example, using data for 1948-92, Curtis and Hastenrath (1995) reported a north-south mean difference ranging from -1.6 to 1.8°C in June to August. For the NwScAT84 run, the north-south SST difference ranges from 0 to 4°C for June to August. The large magnitude of SST gradient used here might amplify the result but would likely give the correct sign of atmospheric response to SST forcing. The Atlantic Ocean basins used here to compute the gradient do not extend to western Atlantic as defined by Curtis and Hastenrath (1995). Moreover, the south Atlantic domain (Fig. 6.6) extends farther east in order to cover the positive SST anomalies off the western coast of southern Africa (present Fig. 6.8, Fig. 2 of Lamb and Peppler 1992).

Warmer north Atlantic and cooler south Atlantic SSTs (NwScAT84) enhance rainfall over northwestern Ethiopia and southern Eritrea (Fig. 6.12e). However, rainfall is reduced over central and northeastern Ethiopia. Examination of the monthly simulated rainfall for the NwScAT84 run indicates that rainfall was deficient in June and July but abundant in August. On the other hand, the simulation with the reversed SST gradient (i.e., cooler than average SSTs over the northern Atlantic and warmer than average in the south) appears to reduce the negative rainfall departures in west-central and eastern Ethiopia and produce slightly wetter conditions in eastern Ethiopia (Fig. 6.12f). The NcSwAT84 simulation also reduced the large positive rainfall departures produced by the NwScAT84 simulation in northern Ethiopia (Fig. 6.12e). A clear difference between the two simulations emerges when monthly rainfall departures are examined. Inspection of the simulated monthly rainfall shows that the NcSwAT84 run gave copious rainfall over much of Ethiopia and southern Eritrea in June and September, but produced deficient rainfall in August.

The maximum effect of these contrasting simulations occurs in August (Fig. 6.13). Noting the similarity of SST gradients in NcSwAT84 and ACTL84 (e.g., Figs. 6.8, 6.9), the simulation results of the NwScAT84 (Fig. 6.13a) and NcSwAT84 (Fig. 6.13b) runs demonstrate the impacts of anomalous northern (southern) Atlantic warming (cooling), respectively, on Ethiopian rainfall in 1984. In particular, the simulated abundant rainfall in June (e.g., Fig. 6.14 for NcSwAT84) and deficient rainfall in August (Fig. 6.13b) for the NcSwAT84 simulation compared to the CTRL84 run are consistent with the 1984 observed above normal all-Ethiopian rainfall for June (not shown) and extreme deficiency in August (Fig. 6.5b). Note also that the regions of negative rainfall departure in



FIGURE 6.13. Departures of August simulated rainfall from the CTRL84 run values for (a) NwScAT84 and (b) NcSwAT84 experiments. Fig. 6.6 and Table 6.2 provide the details of the experiments. Units are mm d<sup>-1</sup>.

August for the NcSwAT84 simulation cover the western escarpments of the Rift Valley, and extend to northern Ethiopia, essentially covering the region that was most affected by the 1984 Ethiopian drought. Considering the significant deficient rainfall in August for the NcSwAT84 simulation (Fig. 6.13b) and the relatively large positive rainfall departures in August for the SATw84 and ATw84 simulations (not shown), the northern and southern tropical Atlantic SSTs and SST difference between the north and south Atlantic appear to be important for Horn of Africa rainfall. In addition, the observational analysis (Fig. 3.4) and the above modeling results are consistent, and indicate that SST variations across the Atlantic maximally affect Horn of Africa rainfall in August. This issue will be examined later in this section. Figure 6.14 compares model rainfall averaged across 100 Ethiopian raingauge station locations for simulations forced by SST variations over the Atlantic and the Mediterranean Sea. Most experiments involving Atlantic SST forcing show strong effects on July, August, and September rainfall, but appear to have little effect on June rainfall. Compared to the CTRL84, the warming of the Atlantic south of 10°N tends to reduce (increase) Ethiopian rainfall in July/September (August). The reduction in rainfall in July for the ATw84 simulation appears to be caused by the warming in SAT since the EqATw84 simulation only marginally affects July rainfall (Fig. 6.14).

In all three simulations (i.e., the EqATw84, SATw84, and ATw84), Ethiopian September rainfall is reduced. Conversely, enhancement of September rainfall appears to result from the north-south SST gradient (resulting from the ±1K modification of the 1982-99 average SST) between the northern and southern Atlantic. In fact, both the NcSwAT84 and (especially) the NwScAT84 experiments tend to increase Ethiopian September rainfall. The N-S SST difference exerts marked influence on rainfall at the peak of the monsoon season as evidenced in the substantial change in simulated August rainfall for the NcSwAT84 and NwScAT84 experiments (Fig. 6.13, 6.14). The highest positive August rainfall departure is associated with the MDTRw84 simulation (Fig. 6.14). It is interesting to note that compared to all warm simulations, the MDTRw84 produced the lowest simulated September rainfall (Fig. 6.11, 6.14).



FIGURE 6.14. Same as Fig. 6.11 except for the Atlantic Ocean and the Mediterranean Sea.

The importance of the north-south SST gradient over the Atlantic is further examined in Fig. 6.15, which shows the time evolution of the interhemispheric SST difference (N minus S, Fig. 6.15a) between the NtAT and StAT (Fig. 6.6) for all SST forcings in the Atlantic. The corresponding simulated rainfall is shown in Fig. 6.15b. The simulated rainfall was constructed by averaging model rainfall interpolated to raingauge locations for individual months as discussed earlier.

The N-S SST differences corresponding to the NwScAT84 and NcSwAT84 experiments form the extreme bounds enveloping the N-S SST differences of the observed 1984 OISST as well as the N-S SST differences for the other experiments (Fig. 6.15a). The N-S SST differences for the EqATw84 and SATw84 experiments



FIGURE 6.15. (a) Evolution of SST difference (K) over the Atlantic Ocean computed as the difference of average SST for the north tropical Atlantic ( $10^{\circ}-35^{\circ}N$ ,  $22^{\circ}W-15^{\circ}E$ ) and south tropical Atlantic ( $0^{\circ}-20^{\circ}S, 22^{\circ}W-15^{\circ}E$ ) for simulations forced by SST variations over different ocean basins in the Atlantic for 1984 as described in the text. (b) Time series of simulated monthly rainfall (mm d<sup>-1</sup>) corresponding to SST forcing in (a). Fig. 6.6 and Table 6.2 provide the details of the experiments.

are identical because neither modifies SSTs over the northern Atlantic, and the southern Atlantic domain either includes grid values of climatology plus 1K north of 0-10°S for the EqATw84 calculation or climatology plus 1K between 10-20°S for the SATw84 case. Thus, in each case, an equal number of grid point anomalies of 1K SST is used.

Inspection of Fig. 6.15 reveals a striking parallel in the simulated monthly rainfall amounts and N-S Atlantic SST differences in August. As in the N-S SST difference, the NwScAT84 and NcSwAT84 simulated rainfall amounts form the extreme limits of the other simulated rainfall amounts. This indicates that warmer SSTs in the northern Atlantic combined with cooler SSTs in the south increase the Ethiopian summer rainfall, but cooler waters in the north and warmer waters in the southern Atlantic appreciably decrease Ethiopian rainfall in August, as occurred in 1984. Because the tropical north Atlantic tends to become anomalously warm during the warm phases of the ENSO, (e.g., Curtis and Hastenrath 1995), the NwScAT84 and NcSwAT84 experiments indicate that the Atlantic Ocean acts to oppose the impacts of the Pacific SSTs on Ethiopian August rainfall. The N-S SST difference appears to have little influence in June. In contrast, the simulated rainfall for September shows wide differences, indicating influences other than the N-S SST gradient (e.g., magnitudes of SST). Note also that, although the EqATw84 and SATw84 have an identical N-S SST

difference, the simulations are forced by different SST patterns since the ±1K anomalies modify the 1982-99 average SST in different regions.

#### 6.3.5 Sensitivity to Atmospheric Boundary Conditions

As indicated earlier, the sensitivity of model simulations to atmospheric boundary conditions is assessed by applying identical SST specifications but changing the atmospheric initial and boundary conditions. Thus, the SST specifications for the CTRL84, ACTL84, EqIOw84, and EQgrdIO84 again were applied, but the 1984 initial and boundary atmospheric conditions were replaced by the NCEP/NCAR Reanalysis data for 1996. Fig. 6.16 shows the resulting simulated June-September rainfall for the CTRL96, ACTL96, EqIOw96, and EWgrdIO96 simulations.

The CTRL96 simulated rainfall is wetter than its CTRL84 counterpart (note the areas covered by the 4-12 mm d<sup>-1</sup> contours in Figs. 6.7a versus 6.16a). As the two simulations differ only by the atmospheric boundary conditions, the wetter condition in CTRL96 is primarily a reflection of the favorable flow patterns in 1996. Segele and Lamb (2005) documented the differences in the large-scale flow in 1984 and 1996. In contrast to the large negative departures noted in the 1984 case, the ACTL96 simulated rainfall is wetter than the CTRL96 simulated rainfall (Figs. 6.7b versus 6.16b); the large discrepancy between the two years, however, is a result of combined atmospheric and oceanic effects.



FIGURE 6.16. Spatial patterns of simulated precipitation and difference fields. (a) Simulated precipitation for the CTRL96 (contours are drawn every 4 mm d<sup>-1</sup>). (b) Difference between ACTL96 and CTRL96 (ACTL96 minus CTRL96) simulated precipitation for June-September 1996. (c) Same as (b) except for EqIOw96 simulation. (d) Same as (b) except for EwgrdIO96 run. Fig. 6.6 and Table 6.2 provide the details of the experiments. Units are mm d<sup>-1</sup>.

Figs. 6.16c and 6.16d show interesting results that support our above assessments and conclusions of the effects of SST variations over the Atlantic and Indian Ocean. Fig. 6.16c and Fig. 6.16d are the counterparts of Fig. 6.10b and Fig 6.10c, which result from the specifications of warmer SSTs over the equatorial Indian Ocean and an east-west gradient with warming (cooling) over the western

(eastern) Indian Ocean. Despite the significant differences in the large-scale flow patterns in 1984 and 1996 (Segele and Lamb 2005, Figs. 15-16), the EqIOw96 and EWgrdIO96 experiments reflect the major rainfall characteristics simulated by the EqIOw84 and EWgrdIO84 runs, respectively. For example, comparing Fig. 6.7b and Fig. 6.16c, we note that both simulations show wetter rainfall conditions especially over the equatorial regions of Ethiopia and Kenya. This feature is produced only by the EWgrdIO simulation. Note also the striking similarity between Fig. 6.7c and Fig. 6.16d, both of which reflect the effects of Equatorial Indian Ocean warming; excessive rainfall over western Ethiopia, wetter conditions over the Rift Valley and eastern Ethiopia, and deficient rainfall over west-central Ethiopia. The striking similarity among these simulations of vastly differing atmospheric boundary conditions but identical SST forcing gives further confidence in the validity and generality of the overall results of the sensitivity studies discussed earlier.

# 6.4 Circulation Changes Corresponding to Warming/ Cooling over the Equatorial Indian Ocean

The atmospheric response to SST forcing over the Indian Ocean is examined by focusing on circulation changes associated with the equatorial Indian Ocean warming/cooling (EqIOw84/EqIOc84). As noted in Section 6.3.3, warming (cooling) of the Indian Ocean generally enhances (reduces) rainfall over the Horn of Africa. The contrast between simulated rainfall for warm and cool equatorial Indian Ocean is highest in July (Fig. 6.17).



FIGURE 6.17. Departures of July simulated rainfall from the CTRL84 run values for (a) EqIOw84 and (b) EqIOc84 runs. Fig. 6.6 and Table 6.2 provide the details of the experiments. Units are mm  $d^{-1}$ .

For the warm equatorial Indian Ocean (EqIOw84) run, most areas of the Horn of Africa except west-central Ethiopia experienced wetter conditions, with the largest positive departure being over western Ethiopia. In contrast, except at a few locations, the cool equatorial Indian Ocean (EqIOc84) experiment produced drier conditions in the region compared to the CTRL84 run. The largest negative rainfall departures are over northeastern Ethiopia and southern Eritrea. Because the maximum difference between the two simulations is in July, the circulation patterns corresponding to the EqIOw84 and EqIOc84 runs are contrasted with the CTRL84 simulation for this month. Since the atmosphere response to warm/cool sensitivity simulations are examined relative to the CTRL84
experiment, the main features of the simulated large-scale atmospheric circulation of the CTRL84 run are presented to facilitate the discussion on the departure fields of the sensitivity experiments from the CTRL84 run (simulated values for warm/cool experiments minus CTRL84 run values). First, the ability of the CTRL84 simulation to reproduce the main monsoon flow is examined. This is followed by a concise assessment of the vertical cross sections of simulated (CTRL84) horizontal winds, specific humidity, and horizontal divergence.

To assess if the simulation forced by the 1982-99 average SST produces the major monsoon features, the large-scale flow patterns for the CTRL84 experiment (Fig. 6.18) are qualitatively compared with the mean seasonal (May-October) reanalysis fields discussed in Chapter 3 (Fig. 3.1). There is a strong similarity between the observed mean seasonal flow (Fig. 3.1) and the modeled flow forced by the climatological SSTs. The primary differences between the July CTRL84 simulated flow (Fig. 6.18a) and the mean seasonal patterns (Fig. 3.1) at 850 hPa are the strengthening of the LLJ, the strong westerlies west of Ethiopia, and the dry northwesterlies along the Red Sea. In particular, the westerlies extending from West Africa to northwestern Ethiopia and the LLJ off the Somali coast are stronger in the CTRL84 simulation compared to the May-October 1970-99 average. At 200 hPa, the easterly flow in the tropics (10°S-20°N) for the July CTRL84 simulation shows good correspondence with the May-October long-term average, but the easterlies in Fig. 6.18b are stronger than the seasonal



FIGURE 6.18. (a) Horizontal wind vectors (arrows; scale at the right bottom corner) and resultant wind speed (contours) at 850 hPa for the July CTRL84 simulation (Fig. 6.6, Table 6.2). (b) Same as (a) except for 200 hPa. Units are m s<sup>-1</sup>. Contour interval is 10 m s<sup>-1</sup>.

means, especially over Ethiopia where they exceed 30 m s<sup>-1</sup>. Furthermore, the simulated flow locates the center of the northern subtropical hemisphere anticyclone over Iraq/Iran, north of its climatological mean position. These changes are expected because the mean May-October flow is strongly smoothed by the averaging as well as by including May and October fields, which exhibit weaker monsoon characteristics. Overall, the major monsoon characteristics are captured well by the CTRL84 simulation.

Figure 6.19 shows a north-south vertical cross section of meridional wind (contour; m s<sup>-1</sup>) and specific humidity (shaded; g kg<sup>-1</sup>) averaged across the longitudinal center of Ethiopia (between 38°-40°E) for July CTRL84 simulation. To approximate the surface elevation, the longitudinally and temporally averaged model surface pressure is shown. The model locates the strongest southerlies near the surface south of Ethiopia (~1-2°N) and the strongest northerlies in the lower troposphere (~ 700 hPa) in Eritrea (~15-17°N).

The location and vertical slope of the ITCZ can be identified by the kinematic axis (meridional wind discontinuity) and the tighter moisture gradient north of 15°N (Fig. 6.19). On the other hand, although the meridional wind discontinuity reaches the surface north of 10°N, which is probably a result of recurving southwesterlies over northern Ethiopia (e.g., Fig. 6.18a), there is little latitudinal moisture change across much of Ethiopian latitudes between 6-14°N. Thus, the



FIGURE 6.19. Meridional-vertical transect of meridional wind speed (contour, northerlies dashed; m s<sup>-1</sup>) and specific humidity (shading; g kg<sup>-1</sup>) averaged over 38°-40°E in July for the CTRL84 simulation (Fig. 6.6, Table 6.2). Temporally and longitudinally (38°-40°E) averaged model surface pressure (hPa) is used to approximate surface elevation (gray shading).

surface confluence line must be located north of Ethiopian latitudes. This conclusion is supported by the observational analysis of Section 3.3.1 (e.g., Fig. 3.2b). Another interesting feature of Fig. 6.19a is the center of maximum southerlies in the upper troposphere north of about 17°N. These southerlies are part of the diverging easterlies of the TEJ at 150 hPa (e.g., Fig. 6.18b).

The vertical profiles of zonal wind and convergence/divergence fields for CTRL84 are shown in Fig. 6.20. The westerlies are shallower in the west but



FIGURE 6.20. East-west vertical (1000-80 hPa) transect of zonal wind (contour; m s<sup>-1</sup>) and horizontal divergence (shading;  $x10^{-5}$  s<sup>-1</sup>) averaged over 8°-15°N for the July CTRL84 simulation (Fig. 6.6, Table 6.2). Dashed lines indicate easterly winds. Isotach spacing is 5 m s<sup>-1</sup>. Temporally and latitudinally (8°-15°N) averaged model surface pressure (hPa) is used to approximate surface elevation (gray shading).

deeper in the east on the western fringes of the LLJ (note the eastward upwards sloping of the zonal wind contours). These westerlies are overlain by the easterly wind regime that maximizes at the 150 hPa, a result consistent with the findings of Segele and Lamb (2005). A north-south vertical cross section of zonal wind shows that the core of the TEJ spans a broad latitudinal belt in July but concentrates between 10°-12N° in August.

Shallow low-level convergence/divergence covers eastern Ethiopia/northern Rift Valley (Fig. 6.20). A thick layer of mid-to-upper tropospheric divergence extends from about 750 to 100 hPa above the escarpments where strong convection initiates. The situation changes for the western regions, which are dominated by shallow low-level divergence and deep mid-to-upper level convergence extending up to 150 hPa. The convergence pattern remains largely unchanged when varying the latitudinal belt (subzones within 8°-15°N) for averaging. Inspection of the divergence field at different levels revealed upper level divergence between 100-80 hPa west of 38°E. It is to be noted that western Ethiopia is one of the wettest regions totaling more than 1800 mm a year, of which more than 90% is received during May-October (e.g., Fig. 1 of Segele and Lamb 2005). A significant part of this rainfall comes from westward propagating storms that are initiated in the east rather than from locally developed convection. It appears that the deep layer of low-to-mid tropospheric convergence and elevated upper tropospheric divergence may be instrumental in maintaining the towering storms that probably overshoot into the lower stratosphere.

With the above background, the changes in the atmospheric circulation associated with the warming/cooling of the equatorial Indian Ocean SSTs now are examined. Departure fields are calculated as the difference between EqIOw84/EqIOc84 simulations and the CTRL84 run values. The low-level

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atmospheric response to the equatorial Indian Ocean warming is captured by the horizontal wind difference between the EqIOw84 and CTRL84 simulations (EqIOw84 minus CTRL84 values) at 850 hPa (Fig. 6.21a). A high-resolution version of the departure field is given in the regional map in Fig. 6.21b.

Compared to the CTRL84 run, the EqIOw84 simulation strengthens the westerlies across western and central Africa. With reference to Fig. 6.18a, this indicates enhanced westerlies entering western Ethiopia (Figs. 6.21a,b). The strongest departure winds (magnitudes of slightly less than 5 m s<sup>-1</sup>) are along the Red Sea coast, and correspond to the anomalous cyclone in northern Sudan. This anomalous cyclonic circulation is a reflection of enhanced southwesterlies across northwestern Ethiopia/Eritrea (Fig. 6.21b) and increased northerly/northeasterly trades over Egypt/northern Sudan. This flow creates a strong ITCZ north of Ethiopia. The increased westerlies from the Atlantic/West Africa appear to weaken the diverging southeasterlies in southern Ethiopia/southern Sudan/northwestern Kenya.

In sharp contrast, the EqIOc84 simulation produced weak westerlies from the tropical Atlantic/West Africa at 850 hPa, resulting in easterly anomalies west of Ethiopia (Fig. 6.22). Another profound difference from the EqIOw84 simulation is the strong anomalous southeasterlies in the equatorial Indian Ocean extending to the coast of Somalia.

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FIGURE 6.21. (a) Horizontal wind departure vectors (m s<sup>-1</sup>; scale at the bottom right) at 850 hPa for the July EqIOw84 run. Departures are calculated as EqIOw84 simulation values minus CTRL84 run values. For clarity, vectors are shown every 4 model grids. (b) Same as (a) except for high-resolution regional map showing departure vectors for all model grids. Fig. 6.6 and Table 6.2 provide the details of the experiments.



FIGURE 6.22. (a) Same as Fig. 6.21a except for the EqIOc84 simulation. (b) Same as Fig. 6.21b except for the EqIOc84 simulation.

The easterly/southeasterly anomalies over the equatorial Indian Ocean in Fig. 6.22 are the result of strengthened southeasterlies that cross the equator with a weaker westerly component. Compared to the CTRL84 flow, the latitude of recurvature in the equatorial Indian Ocean is shifted to the north. The weakened westerlies in the Arabian Sea imply reduced rainfall for Ethiopia as discussed in Chapter 3. Note that parts of the strong southeasterly anomalies west of 35°E and south of 10°N in Fig. 6.22b strengthen the southeasterlies there (e.g., Fig. 6.18a). Also, the southeasterly/easterly anomalies are stronger to the west of 35°E than to the east of 40°E, thereby accentuating the directional wind divergence in southern Ethiopia (e.g., Fig. 6.18a). Thus, because of the existence of the LLJ, the stronger southeasterly anomalies to the west of 35°E imply stronger low-level divergence not only over the climatologically dry southern and southeastern lowlands but also over the wet regions in southwestern Ethiopia.

In the upper levels, the contrast between the EqIOw84 and EqIOc84 simulated horizontal winds is stronger between 300-150 hPa. The difference between the EqIOw84 and CTRL84 horizontal wind vectors for 200 hPa is shown in Fig. 6.23a. The corresponding difference map for the EqIOc84 run is given in Fig. 6.23b. The EqIOw84 simulation has produced stronger easterlies to the west and north of Ethiopia and weaker easterlies over the Indian Ocean. The result is easterly departures to the west of Ethiopia and westerly departure fields to the east in the western Indian Ocean south of 10°N. This flow configuration has



FIGURE 6.23. Same as Fig. 6.21a except for 200 hPa. (b) Same as Fig. 6.22a except for 200 hPa. Resultant departure wind magnitudes are contoured every 5 m s<sup>-1</sup>.

created strong upper level divergence (Fig. 6.24a) and enhanced rainfall over much of the Horn of Africa (Fig. 6.17a). In contrast, the EqIOc84 experiment caused easterly departure vectors over the Indian Ocean and westerly departure winds west and north of Ethiopia (Fig. 6.23b). This enhances easterlies east of 50°E and south of 10°N, but weakens the TEJ across Northeast Africa and Arabian Peninsula. Weakened (strengthened) TEJ to the west and north (east) of Ethiopia corresponding to cooler Indian Ocean SST results in reduced upper level divergence (Fig. 6.24b) and consequently decreased July rainfall across much of the Horn of Africa (Fig. 6.17b). The upper level convergence in southwestern Ethiopia for the EqIOc84 simulation (Fig. 6.24b) further supports effects our earlier assessment of the of increased lower level southeasterly/easterly anomalies for the EqIOc84 simulation. Thus, the EqIOc84 simulated flow at both lower and upper levels favor drier conditions in the climatologically wet regions of Ethiopia.

In general, the main characteristics of the large-scale circulations for the different simulations involve changes in low-level flow patterns, especially in the westerlies from West Africa and the LLJ off the coast off Somalia. Significant changes also occur in the wind structure at upper levels, the primary effects being reflected in the strength of the TEJ, which affects the intensity and distribution of upper level divergence, and possibly the westward propagation of convective storms that develop over the Yemen highlands. A more

comprehensive assessment of the changes in the large-scale patterns associated with the various SST forcings would require a chapter of its own and is left for a future study.



FIGURE 6.24. Departure maps of horizontal divergence  $(x10^{-5} \text{ s}^{-1})$  at 200 hPa calculated as (a) EqIOw84 simulation values minus CTRL84 run values, and (b) EqIOc84 simulation values minus CTRL84 run values. Fig. 6.6 and Table 6.2 provide the details of the experiments.

# 6.5 Effects of Vegetation Coverage on Precipitation

As discussed in Chapter 2, numerous studies have indicated that changes in vegetation coverage and properties can affect local climate and circulation patterns through changes in surface-atmosphere fluxes of water, momentum, and energy. Vegetation can be affected by prolonged dryness. The extremely dry conditions observed in the 1984 spring in Ethiopia had the potential to desiccate the vegetation and alter the vegetation canopy on a large-scale. This prompted

the question--if the failure of the short rains dried vegetation on a massive scale, could that change play a role in the observed total failure of the 1984 summer rains in Ethiopia? This issue is addressed through simple sensitivity tests using the RegCM3. However, this investigation is limited in its scope and aims only to identify the effects of vegetation changes on rainfall, and does not attempt to investigate the large-scale circulation changes or the surface-atmosphere exchanges of water and energy associated with the sensitivity experiments.

#### 6.5.1 Experimental Design

As noted in Section 5.1.2, the RegCM3 uses BATS to describe land use characteristics. The vegetation layer of BATS has 19 land cover types including deserts, grasses, shrubs, and trees. Fig. 6.25 shows the default BATS land cover type (excluding the ice cap/glacier category) over the Horn of Africa. Each category has specified characteristics including vegetation albedo, maximum fractional vegetation cover, soil texture and color types, and roughness length, which affect the surface-atmosphere exchanges of energy, water, and momentum. In addition, soil moisture is initialized according to the vegetation specification (e.g., Pal et al. 2005). For example, the soil moisture availability for desert is 10% while for bog or marsh it is 90%.

The effect of vegetation cover on precipitation is assessed by examining the impact on simulated rainfall resulting from changes in the specification of

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FIGURE 6.25. Default land cover type used in RegCM3.

vegetation types for the region between 8°-18°N and 32°-45°E, where the effects of the failure of the short rains would have especially been strong. This strategy is analogous to what Xue and Shukla (1993, 1996) used in their sensitivity studies in which they changed the land surface condition in the Sahel into desert/broadleaf trees (forest) to investigate the impacts of desertification/afforestation on the model climatology.

Three simulations were performed for the entire domain shown in Fig. 6.6. The control run uses the default land use described by BATS (Fig. 6.25), and hence has identical vegetation specification as the ACTL84 simulation discussed in Section 6.3. A hypothetical wet simulation was performed by assuming that

wet spring rains would create abundant vegetation before the start of the summer rains. For the wet simulation (WET84), the default vegetation land cover types were changed to reflect wetter conditions that would probably exist if the spring rains were wetter than normal. For this scenario, each land cover type north of 8°N was changed such that the new land cover became greener/less dry, and in most cases the default BATS land cover type was changed at least 1 category up to wetter conditions (Fig. 6.26). For example, desert regions are changed to semi-desert, short grasses are changed to tall grasses, shrubs are changed to trees, and trees are changed to forests. These changes were made after examining the specified values of the vegetation properties such as maximum fractional vegetation cover, vegetation albedo, and leaf area indices. In most cases, the changes increase the maximum fractional vegetation cover and/or decrease the vegetation albedo values. Some categories were left unchanged (e.g., bog/marsh).

Contrasting this specification is the dry simulation (DRY84) in which each land cover was changed to a less green/drier category (Fig. 6.27), corresponding to the situation that might have occurred as a result of the failure of the Ethiopian 1984 short rains. In this case, the default BATS land cover type was changed at least 1 category down to drier conditions, which is the exact opposite of the land cover changes made for the WET84 simulation. This drier specification created a strong land cover contrast compared to the greener landscape corresponding to the default BATS land use.



FIGURE 6.26. Land cover type used for the WET84 simulation.

Each of the three simulations was driven by the OISST monthly data (Reynolds et al. 2002) with the NCEP/NCAR Reanalysis version 1 (Kalnay et al. 1996) initial and time-dependent lateral boundary conditions for 1984. The atmospheric boundary conditions are updated every six hours. The model integration time step, resolution, and physics are the same as for the simulations in Section 6.3. Each run was initialized on May 25, 1984, and run through September 30, 1984. The results of are presented in the next section. Because the boundary conditions and model configuration for the control run are identical to the ACTL84 run, the control simulation is referred to as ACTL84.



FIGURE 6.27. Land cover type corresponding to the DRY84 simulation.

#### 6.5.2 Simulation Results

Simulated rainfall for the WET84 and DRY84 experiments are compared with the ACTL84 simulation values. The ACTL84 run (Fig. 6.28a) locates the main rainfall center in the wetter regions of western Ethiopia. Departure maps were constructed for individual months and for the entire June-September season by subtracting the ACTL84 simulation values from the corresponding WET84 and DRY84 simulation results. Examination of the results for individual months shows that the rainfall response to changes in vegetation cover, reflecting changes in the atmospheric circulation, was strong beginning in July. Fig. 6.28 shows the June-September rainfall departure from the ACTL84 values for the WET84 (Fig. 6.28b) and DRY84 (Fig.6.28c) simulations. Departure maps for July, August, and September, for which the effects of the forcing are most pronounced, are similar to the seasonal departure map and will not be presented. The response to the dry/wet surface forcing is minimal in June.



-4 -3.5 -3 -2.5 -2 -1.5 -1 -0.5 0.5 -10 -51.5 2.5 10 15 1 2 3.5 4 5 3 FIGURE 6.28. June-September simulated rainfall and departure maps. (a) Simulated rainfall (ACTL84) for the default vegetation layer of BATS. (b) Rainfall departure for the WET84 simulation. (c) Same as (b) except for the DRY84 simulation. Departures are computed by subtracting the ACTL84 simulated rainfall from the corresponding WET84 and DRY84 simulated values. Units are mm  $d^{-1}$ .

The simulation for the wet short rains scenario, with the resulting ample vegetation cover, produces enhanced June-September rainfall primarily in the western regions, and reduced rainfall at a few scattered locations in the southwest and east-central and north (Fig. 6.28b). Although the simulation produced more positive departures than negative, the overall signal appears to be mixed. This probably is due to the small difference between the default and modified land cover types or due to the small spatial variation of the physical properties (e.g. albedo) of the modified vegetation cover. Xue and Shukla (1996) also found mixed signals for their GCM sensitivity experiments that investigated the effects of large-scale afforestation in sub-Saharan area on the climate. In their afforestation experiment, Xue and Shukla (1996) changed shrubs and bare soil into broadleaf trees over a large sub-Saharan area extending from 13°N to 20°N. Their result showed that while rainfall increased in much of the afforestation region, it decreased to the south of the region. They further identified surface albedo and cloud cover as the most important factors controlling the changes in land surface-atmosphere interaction. Additional experiments may be needed to understand the causes of the mixed sensitivity results for the Horn of Africa.

On the other hand, Fig. 6.28c shows clear evidence of the effects of reduced pre-monsoon core vegetation cover on rainfall in the Horn of Africa. Except for a few locations in southwestern Ethiopia, drying and reducing the default vegetation cover has resulted in substantial reduction of June-September rainfall over many regions, including northeastern Ethiopia where the highest June-September deficient rainfall was observed in 1984 (e.g., Segele and Lamb 2005). Because there is a direct correspondence between vegetation specification and soil moisture status in RegCM3, the DRY84 simulation is similar to a simulation with decreased soil moisture. Therefore, the result is consistent with a positive feedback mechanism described by Eltahir (1998) for North America, in which decreased initial soil moisture progressively leads to decreased latent heat fluxes, increased sensible heat fluxes, decreased moist static energy, increased stability, and finally decreased precipitation. In general, although the WET84 simulation did not give the opposite result to the DRY84 simulation, i.e., increased rainfall through much of the domain, the results of the simulations collectively suggest that the failure of the 1984 short rains probably had negatively affected the summer monsoon season through its drying effect on vegetation cover. Further examination of the causes of this effect is left for a subsequent investigation.

## 6.6 Summary

This chapter has investigated the effects of SST variations through observational analyses and model sensitivity experiments. The observational results showed a strong simultaneous relationship between Ethiopian rainfall and SSTs over the equatorial eastern Pacific. However, this relationship does not have significant seasonal forecasting value, because of the lack of lead time. In order to forecast June-September rainfall, it is necessary to know Pacific SSTs in

advance for that season. This requires predicting SSTs to forecast rainfall, thereby introducing errors that reduce the skill obtained from the concurrent SST-rainfall relationship. With errors introduced by projecting current SST magnitudes to values the Pacific Ocean probably would have in summer, the equatorial Pacific SST no longer relates to rainfall as strongly as the observation analysis indicates. The other alternative is to use observed SSTs recorded more immediately prior to the onset of the monsoon season in Ethiopia. However, the correlations between equatorial Pacific SST prior to the onset of the monsoon and Ethiopian summer rainfall is not strong because of the boreal spring predictability barrier of climate system in the tropics (e.g., Webster et al. 1998; present Fig. 6.1). On the other hand, the correlation between the Arabian Sea SST a year in advance and Ethiopian summer rainfall is stronger than the correlation between equatorial eastern Pacific SST for any month except August-October of current year and Ethiopian JJAS rainfall. Therefore, the Arabian Sea SST has greater potential predictive value for forecasting seasonal Ethiopian rainfall with lead times that Ethiopian society can exploit.

The model sensitivity experiments reported in this chapter have highlighted the relative importance of SST variations in several basins of the Atlantic and Indian Oceans and the Mediterranean Sea. The effects of these water bodies vary considerably in space, time, and strength. Furthermore, not only the absolute SST magnitudes, but also the presence of basin-scale north-south/east-west gradients is important in shaping seasonal rainfall in the Horn of Africa. In particular, a north-south SST gradient over the tropical Atlantic exerts a strong influence on August rainfall. Both observational and modeling studies showed that cool northern (warm southern) tropical Atlantic significantly reduces Ethiopian rainfall. In fact, model sensitivity experiments indicated that the 1984 Ethiopian dry summer was partially a result of such SST distribution in the tropical Atlantic. On the other hand, warm northern (cool southern) tropical Atlantic tends to favor wetter conditions in the Horn of Africa. Because the northern tropical Atlantic tends to be warmer than the southern tropical Atlantic during El Niño, this result implies that during the warm ENSO phase, SST variations in the Atlantic tend to counter the effects of warm equatorial eastern Pacific SSTs on Horn of Africa rainfall.

Warming in the Arabian Sea, the equatorial Indian Ocean, and the Mediterranean Sea tend to enhance summer rainfall in the Horn of Africa. The effects of the Mediterranean Sea and the Arabian Sea warming are pronounced in August, while the impact of the equatorial Indian Ocean tends to be felt more strongly in July. While SST variations in the Indian Ocean strongly affect the extreme western Ethiopia, the effects of the Mediterranean Sea are pronounced over central Ethiopia. Model sensitivity experiments also showed that warming of the equatorial Indian Ocean strengthen the LLJ, the westerly low-level flow from West Africa, and the TEJ. In contrast, these large-scale features are weakened when the equatorial Indian Ocean is cooler than average. Model sensitivity tests further indicated that an east-west SST gradient in the equatorial Indian Ocean primarily affects rainfall in September. In particular, warm (cool) western (eastern) equatorial Indian Ocean cause widespread rainfall in climatologically dry regions of southern and southeastern Ethiopia and equatorial regions of Somalia and Kenya. The implication of the results of the above modeling experiments is that a successful seasonal forecasting scheme needs to take into account the effects of/contributions from each ocean basin in forecasting rainfall over the Horn of Africa.

The influence of vegetation type and status on rainfall amount and distribution also has been investigated in Chapter 6. In brief, the simulations suggest a reduced vegetation cover leads to an increasingly dry landscape. It was found that a vegetation degeneration due to a weak spring rains is likely to reduce the summer monsoon rainfall, especially in regions that typically receive less rainfall. However the opposite situation, enhanced vegetation coverage and status, does not necessarily increase rainfall across the region of lush vegetation. An important implication of this result is that, because of the demonstrated sensitivity to vegetation coverage, an accurate representation of the vegetation canopy is crucial for a successful utilization of RCMs for seasonal forecasting over this region.

## **CHAPTER 7: SUMMARY AND CONCLUSIONS**

## 7.1 Summary

The Horn of Africa is one of the least developed regions of the world, where rain fed agriculture and livestock raising are the main sources of livelihood. June-September is the main rainfall season for a large portion of the region. In recent decades, the region has experienced devastating droughts and occasionally damaging floods. Despite the catastrophic climate-related calamities, the region's weather, climate, and their variability are not well understood.

Based on simple correlation, regression, and composite analyses, the relationships between Ethiopian rainfall and the large scale atmospheric circulations covering Africa, the Atlantic, and Indian Ocean have been identified. The following atmospheric features lead to or are associated with enhanced regional rainfall. The opposite atmospheric features are associated with drier conditions:

 Deep monsoon trough at the surface and lower geopotential heights extending up to 700 hPa over the Arabian Peninsula and India (10°-30°N,30°-85°E); lower surface pressure and lower near-surface geopotential heights below 925 hPa over West Africa (20°-25°N, 10°W-0°);

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- 2. A strong meridional ridge along the Mozambique channel and higher pressure over the Gulf of Guinea;
- 3. Higher geopotential heights between 10°-30°S and west of 50°E extending from the surface up to 700 hPa;
- 4. Higher geopotential heights north of 15°N in the middle-to-upper troposphere (500-150 hPa);
- 5. A strong Low Level Jet (LLJ) north of 10°N at 850 hPa; strong northerlies along the Red Sea and surrounding regions;
- 6. Strong westerlies over eastern Ethiopia and the Gulf of Aden at 850 hPa; strong easterlies over the equatorial Indian Ocean (4°S-0°;55-68°E) at 850 hPa;
- 7. Cooling at 500 hPa over Ethiopia;
- 8. Warmer tropospheric temperatures between 20°-40°N extending from the surface up to 200 hPa, and cooler lower tropospheric temperatures over the western Indian Ocean, the Atlantic, and over much of Africa south of about 15°N excluding the Congo basin;
- 9. Strong upper level easterlies over the monsoon regions with northerlies over Sri Lanka/southern India at 150 hPa.

Other important findings from the observational analyses include:

1. At the height of the monsoon season, the surface position of the ITCZ is north of Ethiopia.

- 2. The effect of the Mascarene high on Ethiopian rainfall is the highest when it is west of about 70°E. Ethiopian rainfall is more strongly related to sea level pressure changes over the Gulf of Guinea than over the southern Indian Ocean, excluding the Mozambique Channel.
- 3. The influence of southern hemisphere winter atmospheric systems on Ethiopian rainfall generally weakens above 700 hPa, but the northern hemispheric systems north of 15°N above 700 hPa begin to exert stronger influence on the Horn of Africa weather.
- 4. There is no statistically significant linear association between Ethiopian rainfall and atmospheric circulation features over the equatorial Pacific on short time scales.

Because of the nonlinear nature of atmospheric processes, rainfall variations are determined by the nonlinear interactions of several atmospheric/oceanic processes that occur at different time and spatial scales. To assess rainfall variability and the forces that affect it at different time scales, a wavelet analysis technique was applied to Ethiopian raingauge, the NOAA Climate Prediction Center (CPC) Merged Analysis of Precipitation (CMAP) rainfall estimates for the entire Horn of Africa, sea surface temperature (SST), and several atmospheric variables. The analysis identified and isolated the dominant modes of rainfall variability and the corresponding atmospheric and oceanic features that are described below. Examination of the power spectra associated with the 5-day May-October Ethiopian rainfall showed that there are distinct temporal modes of rainfall variability covering a wide range of frequencies ranging from the intraseasonal to multidecadal and longer time scales, of which the annual cycle constitutes the primary mode of variability over the Horn of Africa. The power spectra for June-September 5-day rainfall is similar to that for May-October rainfall, except that (1) the power associated with the annual cycle becomes less prominent, (2) there is strong spectral power at the intraseasonal time scale, and (3) there are two distinct modes corresponding to rainfall variability at the biennial and ENSO time scales. The main results from the wavelet analysis are the following:

- Moisture and local circulations appear to be important factors influencing rainfall on the intraseasonal time scale (15-75 days). In addition, no link was found with the Madden-Julian Oscillation (MJO). Further study is required to identify clearly regional circulations that explain rainfall variability at this time scale.
- 2. Rainfall variations with periods from 75-230 days tend to be affected by pressure changes over the tropical Atlantic Ocean and Arabian Peninsula. Wet monsoon conditions are characterized by a southwest-northeast directed pressure gradient associated with a general pressure fall over the Arabian Peninsula and pressure rise over the Gulf of Guinea. Associated with this anomalous pressure configuration,

westerly wind anomalies accelerate into Ethiopia and create an enhanced region of low-level convergence along the Red Sea.

- 3. Rainfall variability associated with the annual cycle (0.6-1.5 year) exhibits the largest variance and the highest correlation signals with atmospheric fields. Among the fields examined, the TEJ exerts the highest impact on rainfall, with strongest correlation between easterlies and rainfall being -0.97. Likewise, SST changes over several ocean basins including the western Indian Ocean, the Gulf of Guinea, and the South China Sea strongly influence rainfall ( $\mathbf{r} \sim |0.8|$ ).
- 4. At the biennial/ENSO time scales (1.5-4.4 year), the largest regional atmospheric anomalies affecting rainfall occur over the southeastern tropical Indian Ocean, the northeastern Atlantic, the western Mediterranean, and the Arabian Peninsula. During the cold ENSO phase, the Azores high strengthens, the mid-latitude westerlies across the Mediterranean weaken, the monsoon trough over the Arabian Peninsula deepens, and pressure over the eastern/southeastern Indian Ocean falls. The decrease in pressure over the eastern/southeastern Indian Ocean parallels the increase in pressure over the southern tropical Pacific, and hence is part of the SOI phenomenon.
- 5. The relationships between Ethiopian rainfall and equatorial Pacific SSTs at the biennial and ENSO time scales are similar. In both cases, Ethiopian rainfall strongly positively (negatively) correlates with

equatorial western (eastern) Pacific SSTs. However, the effects of Indian Ocean SST on Ethiopian rainfall are different at the biennial and ENSO time-scales. At the biennial time-scale, SST variations over the bulk of the tropical Indian Ocean correlate, if at all, weakly with Ethiopian rainfall, but the situation changes dramatically at the ENSO time scale in which rainfall correlates strongly negatively with SST over much of the tropical Indian Ocean.

Building upon the above results of observational analyses, the predictability of Ethiopian rainfall was assessed for several time-scales and statistical prediction models developed. A forecasting technique that combines linear regression with wavelet analysis was used to develop prediction models that are valid for medium (a week to less than a month) and long range (a month to seasons) forecasts. A nonlinear technique (artificial neural network) was examined but combining the wavelet banding technique with a simple linear regression method was found sufficient to develop very encouraging prediction models for Ethiopia.

For medium range forecasting, data for 1970-89 were used to develop a model capable of forecasting all-Ethiopian average rainfall 20 days in advance from several atmospheric predictors across Africa, the Mediterranean Sea, the Atlantic, and the Indian Ocean. The model was tested on independent data for 1990-99 and found to explain about 63% of the total all-Ethiopian rainfall variance. The SST-based models developed for seasonal forecasts performed even better. These empirical models were developed in two ways: in the first method, regional predictors were selected after evaluating their importance in the rainfall-SST relationship; in the second method, predictors were chosen objectively by employing Principal Component Analysis to reduce the number of predictors to a required level. Both methods produced dependable prediction models for forecasting monthly totals and seasonal anomalies of all-Ethiopian rainfall, and anomalies at a specific location. For monthly and seasonal predictions, the models developed in this study performed exceptionally well in identifying the most extreme years, and greatly outperformed previous linear regression models developed for Ethiopia.

The modeling study first investigated the ability of the RegCM3 to reproduce the observed rainfall amounts and distribution over the Horn of Africa. Exhaustive sensitivity tests were performed to select the best convective scheme applicable for the region. After adapting and validating a suitable model configuration, the interannual variability of the simulated rainfall was assessed. Examination of the results showed that the correlation between the simulated and observed Ethiopian seasonal rainfall for 1982-99 was strong ( $\mathbf{r}$ ~0.66). This configured model was utilized subsequently to investigate the roles of individual ocean basins in the Atlantic and Indian Oceans. The effects of basin-scale SST variations were assessed through observational and model sensitivity experiments. The observational analysis showed that the equatorial Pacific correlates strongly with contemporary Ethiopian rainfall from June to October ( $\mathbf{r} \sim -0.58$  to -0.68). However, this concurrent correlation is of little value to forecast June-September rainfall because the observed SSTs available at the time of the forecast (before the start of the season) must be projected forward in time to June-September. This introduces errors, barring perfect dynamical/statistical SST predictions. On the other hand, the correlation between Arabian Sea SST and June-September Ethiopian rainfall is strong a year before the monsoon starts in Ethiopia ( $\mathbf{r}$ ~-0.65). Thus, Arabian Sea SSTs can readily be used to forecast rainfall a year in advance. No other ocean basin offered such a strong relationship prior to the onset of the rainy season in Ethiopia.

Several sensitivity experiments were carried out with the RegCM3 to assess the roles of SSTs over the Mediterranean Sea, the Atlantic, and Indian Ocean on Horn of Africa rainfall. The experiments used seasonally varying climatological SST forcing for the control run. SSTs then were increased/decreased over selected ocean basins to examine the impact of a specific region. The NCEP/NCAR Reanalysis data for 1984 were used for atmospheric initial and boundary conditions. To examine the sensitivity of the simulation results to atmospheric initial and boundary conditions, some of the simulations were repeated using identical SST forcing, but with atmospheric initial and boundary conditions for 1996. For a given atmospheric initial and boundary conditions, the difference between the simulation for a warmer/cooler ocean basin and the control integration was interpreted as the impact of the warmer/cooler ocean basin. The effects of SST variations in the Mediterranean Sea, the Atlantic, and Indian Ocean basins on Horn of Africa rainfall varied considerably in space, time, and strength. The main results are summarized below.

- 1. The Arabian Sea/northern Indian Ocean (ArbS; 10°-30°N, 40°-80°E) SST strongly impacts rainfall. Compared to the control run, the simulation with warm ArbS produced wetter conditions across much of the Horn of Africa, with the highest positive rainfall departure (warm simulation values minus control run values) occurring in August. The area of positive rainfall departures for the warm ArbS simulation is wider than is the case for the other simulations forced by warm/cool SSTs in the Atlantic and Indian Ocean basins.
- 2. A uniform warming of SST over the equatorial Indian Ocean (IqIO; 10°S-10°N, 40°-110°E) primarily affects central and extreme western Ethiopian rainfall. Warm SSTs in the EqIO enhance rainfall over western Ethiopia and reduce it over the central regions. A uniform EqIO cooling has the opposite effect. On the other hand, a linear east-west SST gradient over the EqIO affects rainfall further south, over the equatorial regions of Ethiopia and Kenya. Warm waters over the

western Indian Ocean and cooler waters in the east enhance rainfall primarily in the southern regions of Ethiopia and Somalia, and northern Kenya. The effect is pronounced in September.

- 3. The southern Indian Ocean (10°S-40°S, 50°-110°E) has similar effects on Horn of Africa rainfall as the EqIO, enhancing rainfall in extreme western Ethiopia/eastern Sudan. On the other hand, a uniform warming of the entire Indian Ocean (40°S-30°N, 40°-110°E) tends to affect the northern and southern half of the region differently, creating drier (wetter) conditions in the north (south), especially at the height of the monsoon season.
- 4. The effects of the Atlantic Ocean are more strongly experienced over north Ethiopia/Eritrea. Its impacts strongly depend on the interhemispheric SST difference. Warmer SSTs over the southern tropical Atlantic (0°-20°S, 22°W-15°E) combined with cooler SSTs over the northern tropical Atlantic (10°-35°N, 10°-22°W) strongly reduce August rainfall over the Horn of Africa. This was the case in the severe drought year of 1984.
- 5. Warm Mediterranean waters (30°-46°N, 5°W-42°E) enhance rainfall in the Horn of Africa. Compared to the control run, the simulation with warmer Mediterranean Sea produced large positive rainfall departures, especially over central Ethiopia in August.

6. Model simulations driven by identical SST forcing but with different atmospheric initial and boundary conditions produced remarkably similar rainfall departure patterns that were attributed to the prescribed SST forcing.

Model sensitivity experiments also were used to investigate the effects of vegetation type and coverage on Horn of Africa rainfall amount and distribution. The study found a strong reduction in rainfall when a more desert-like landscape replaced the default vegetation and land use types. A desert-like landscape was specified to approximate a vegetation degeneration that likely followed the poor early rains of spring 1984. The results highlight the importance of accurate representation of the vegetation canopy for a successful utilization of RCMs for seasonal forecasting.

## **7.2 Conclusions**

This study has comprehensively investigated and documented the weather and climate systems that affect the intraseasonal, interannual, biennial, ENSO, and longer time-scale rainfall variability over the Horn of Africa through observational and modeling analyses. Building on the observational analysis results, dependable forecasting models have been developed using a novel technique that combines wavelet analysis and linear regression methods. The empirical models developed in this study can be used to forecast rainfall amounts and anomalies for a specific location or region for periods ranging from a few days to seasons in advance. The modeling study has established a usable regional model for the Horn of Africa. The sensitivity studies performed have identified the roles of individual ocean basins and local vegetation properties for monsoon rainfall variability for the region. The experiments highlighted the relative importance of SST variations in several basins of the Atlantic and Indian Oceans and the Mediterranean Sea.

In general, this study has both scientific and societal value. Scientifically, the detailed observational analysis of our study addresses one of the major issues Washington et al. (2006) raised concerning the lack of systematic understanding of the basic state of the atmospheric circulation over parts of Africa. The identification, examination, and documentation of the regional and local atmospheric and oceanic features and mechanisms directly linked to Horn of Africa rainfall variability on several time-scales contribute to the understanding of the basic circulation patterns in this little-studied region of Africa. As Washington et al, (2006) noted, such knowledge is essential for improving the management of activities affected by climate variability and future climate change, not only locally but also on a larger scale. The study also has significant societal value. The prediction capability of this study will play a role in reducing the catastrophic impacts of droughts and floods by improving disaster preparedness through early warnings of impending weather/climate conditions.
However, the usability of these prediction models depends on whether the forecasts are target oriented, effectively disseminated, and correctly interpreted. This requires identifying human activities most severely impacted by climate fluctuations by geographic locations and recognizing the most affected regional economic sectors that possess the flexibility to adjust and benefit substantially from seasonal climate forecasts. This is achieved through intensive and continuous interactions among climate scientists, climate information users, and decision makers. Supported by this comprehensive knowledge, the elaborate prediction methods and results of this study can readily be applied to achieve the desired goal.

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