ESTIMATING THE REGIONAL CLIMATE RESPONSES OVER RIVER BASINS TO CHANGES IN TROPICAL SEA SURFACE TEMPERATURE PATTERNS

A Thesis in
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by
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Abstract

The goal of this research is to identify and assess teleconnection signals between climate variables related to hydrologic impacts over different river basins and anomalous sea surface temperature (SST) changes. To investigate this problem, we examine the regional climate sensitivity to forcing by patterns of SST anomaly patterns through a linear relationship given by the global teleconnection operator (GTO, also generally called sensitivity). The study assumes that this operator defines the linear relation between forcing and regional climate response of a target area. The sensitivities are computed from data calculated from a large set of simulations of the NCAR Community Atmospheric Model version 3.1. The validity of the linear method is examined by comparing with both climate model and observational data. We expect the linear method could be used for other applications in related fields, like identifying drought conditions over river basins or river flow forecasting.
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Chapter 1

INTRODUCTION

1.1 Motivation

Seasonal to annual hydroclimate predictions have been developed recently based on ocean-atmosphere teleconnection mechanisms such as El Niño-Southern Oscillation (ENSO) and Pacific Decadal Oscillation (PDO) (Hidalgo and Dracup, 2003; Bracken et al., 2010; Sankarasubramanian et al., 2008; Switanek et al., 2009). Using these hydroclimate predictions, many climate-related impact research institutes have been able to make better seasonal forecasts for climatic variables such as temperature and precipitation than by using numerical prediction models. Successful predictions are based on the ability of climate models to capture the induced physical processes in the atmosphere from sea surface temperature (SST) anomalies which affect the climate system. For example, climate models can now predict how global atmospheric circulation responds to anomalous tropical sea surface temperature (SST), which is highly associated with ENSO phenomenon. Therefore,
even though there might be additional factors that contribute to regional climate predictions, we would like to study how hydroclimatic variables over our specific regions respond to such SST in current models when considering the influence of both non-ENSO related and ENSO related SST anomalies. Furthermore, we would like to know whether we can use those sensitivities to tropical SST anomalies for predicting signals of regional climate change, such as changes in regional hydrologic cycle.

Multi-decadal climate variability of SST anomalies plays a substantial role in influencing local climate of some vulnerable regions because it is the main driver of ocean-atmosphere-land teleconnections that could affect regional hydroclimate (Barlow et al., 2001; Ellis et al., 2010; McCabe and Palecki, 2006; Nigam, 1999; Nigam et al., 2011; Tootle and Piechota, 2006). For instance, many studies have found that SSTs over both Indian and Pacific Ocean influence multi-decadal climate variability over East Africa (Williams and Funk, 2011; Lyon and DeWitt, 2012). SST anomalies can alter the atmospheric circulation through teleconnection processes and bring moist or dry conditions to those regions; thus, it can further raise severe problems related to water resources management, agriculture, economy, human health, etc.

Compared to previous studies, most of which focus on larger scale response over several regions, in this study, we would like to estimate the regional climate responses to anomalous SST patterns over several river basins inspired by the
following studies. Several studies related to regional climate teleconnections for different main river basins or regions have been conducted recently and several examples are provided variability of precipitation across the United States is primarily affected by SST anomalies over the tropical Pacific Ocean and the ENSO phenomenon (Ropelewski and Halpert, 1986). Switanek and Troch (2011) use teleconnection phenomena such as Atlantic Multidecadal Oscillation (AMO) and PDO time series to forecast anomalous streamflow in the upper Colorado River at Lee’s Ferry on decadal timescales. Also, drought events occurring in the southwest of the US are linked to the cold phase of ENSO (Redmond and Koch, 1991; Piechota and Dracup, 1996; Cayan et al., 1999). Furthermore, according to more recent studies, the warm phase of the AMO is related to negative precipitation anomalies over the central and western United States, resulting in droughts in the 1930s and 1950s (Enfield et al., 2001; Hidalgo, 2004; McCabe et al., 2004). From the findings above, Ellis et al. (2010) analyzed the patterns of drought events over the Colorado River basin based on those teleconnection information. Tierney et al. (2013) found that Indian Ocean SSTs have primary impact on East African rainfall over multi-decadal timescales based on the proxy and coupled model evidence. Given the wide interest in this research area, we anticipate the linear approach of this thesis, which will be addressed later, can become a tool to analyze sensitivity of hydroclimate over different river basins to anomalous SST patterns in certain part of the ocean.
Because the impacts of SST variations can be related to regional climate change response via physical mechanisms, the ultimate goal of this research is to identify and assess how hydrologic variables over major river basins depend on the forcing from anomalous SSTs patterns in an atmospheric climate model. In addition, considering the fact that running multiple general circulation models (GCMs) requires large computational and financial resources and policy analyses need large ensembles of predictions to obtain robust and reliable results, we propose to assess the predictability of the climate system by using a linear model and apply this simplified approach to reduce complexity in the predictions of the climate system. We examine key hydro-climatic variables over several target river basins where the goal is to provide a method to assess for expected regional climate change over target regions related to SST variability and thus provide useful information to address questions related to adaptation and vulnerability without underestimating the risk.

1.2 Related Research

The research in this thesis follows the initial of work done by Barsugli and Sardeshmukh (2002), Barsugli et al. (2006), and Li et al. (2012) with adjustments required to apply them to regional hydrologic studies. Barsugli and Sardeshmukh (2002) and Barsugli et al. (2006) first start with investigating the sensitivity of global atmospheric response to anomalous SST patterns over the Indian and Pacific Oceans.
in the tropics, and then they also estimate the linearity of local precipitation response to those SST patterns for various regions in North America and Africa. Li et al. (2012) develop another more efficient method to analyze regional sensitivity of the responses to SST anomaly patterns over different regions across various continents and compared the results to those from Barsugli and Sardeshmukh (2002) and Barsugli et al. (2006). The following sections will review the key literature and highlight the background knowledge associated with this thesis.

1.2.1 Previous Studies

Recent investigations have highlighted the role that SST patterns play in driving the historical and projected regional-scale climate change (Shin and Sardeshmukh (2011); Xie et al. (2010) respectively). Barsugli et al. (2006) further point out that SST trends over tropical regions impact the large-scale response of regional climate change as related to the teleconnection response. Although many factors such as land processes, aerosols, and clouds might affect regional climate, however, we are specifically interested in the role SST variations play in affecting regional climate on seasonal and longer timescales. Shin and Sardeshmukh (2011) highlight the importance of the correct representation of SST changes in climate models in order to characterize their impacts on land areas. They also point out that the successful seasonal to interannual predictions is owing to recognizing the role SSTs play (Goddard et al., 2001; Barnston et al., 2005). These are several reasons why
we would like to consider the impacts of SST patterns on regional climate change and we deem that as a primary factor.

Moreover, we especially focus on the SST patterns in tropical regions. Many studies (e.g. Lau and Nath (1994); Lau (1997); Saravanan (1998); Graham (1994); Hoerling et al. (2001); Hoerling and Kumar (2003); Schneider et al. (2003); Deser et al. (2004)) have demonstrated that the responses to global SST changes can be reproduced in climate models with prescribed SST changes only in tropical ocean. For example, Lau and Nath (1994) perform a set of experiment by running an AGCM with different geographically specified SST conditions as follows: Near-global ocean (GOGA run), tropical Pacific (TOGA run), and midlatitude North Pacific (MOGA run). Their results show that the TOGA experiment is able to reproduce many of the atmosphere-ocean teleconnection phenomena detected by GOGA. However, MOGA runs display a weaker response so that those signals cannot be reproduced.

The comparison between TOGA and MOGA runs further highlights the role tropical SST anomalies play in forcing the midlatitude atmospheric circulation. The results of TOGA experiments provide a basis for explaining how the teleconnection signals are communicated through atmosphere-ocean interactions so that anomalous SST in the tropics can affect the remote atmospheric responses. The physical mechanism of the occurrence of the causal chain of events is discussed next.
The basic mechanism of explaining the influence of SST variability on regional climate via teleconnections is briefly described by the following causal chain of events (see Figure 1.1). The major driver of the atmospheric circulation response is the heat content over upper layer of Tropical Ocean as represented by SSTs. As a climate forcing is applied, the tropical SSTs will change and then force changes in other components of the climate system. The response to those heat source anomalies will be dynamically propagated through the tropics and other regions over the world by perturbations to the Hadley and Walker circulations which can drive planetary Rossby waves. The physical interpretation of sensitivities estimated by the previous studies depend on the understanding of the basic chain of events triggered from tropical SST anomalies to the global atmospheric response in the model. Although many complexities were ignored, the mechanisms of this chain can be illustrated as follows (Sardeshmukh and Hoskins, 1988):

**Figure 1.1:** Schematic figure summarizing the mechanism of the teleconnection chain of events.
Following the flow diagram in Figure 1.1, the impacts of SSTs variations on the atmosphere can be communicated via heat, momentum and moisture fluxes thereby altering the atmospheric circulation. This can result in patterns of variability via teleconnections (Horel and Wallace, 1981; Wallace and Gutzler, 1981) with the underlying transport of heat, momentum, buoyancy, and material by large-scale ocean circulation changes serving as a base. This teleconnection phenomenon transmits climate signals across long distances to remote regions and it can further modify local regional climate processes. Therefore, it is critical to understand how teleconnection signals propagate, and what processes lead to local changes.

Based on the brief discussion above, it can be inferred that for large-scales, the tropical ocean is the primary boundary forcing that drives atmospheric circulation due to SST anomaly patterns triggering vigorous convective activity and localized latent heat release in the upper troposphere. Thus decadal variability found in SST patterns over tropical oceans can produce teleconnection patterns that link regions within the tropics as well as influence the tropical and extratropical regions. Therefore, it is expected that decadal variability of SSTs will affect simulations of regional climate and specific variables of interest. In this way, the sensitivity of specific variables over interested regions can be probed through the sensitivity of atmospheric models to prescribed tropical SST changes.

In order to better represent the impact that tropical SSTs can cause on regional climate, we use an uncoupled AGCM instead of a fully coupled atmosphere-ocean
general circulation model (AOGCM). According to Shin and Sardeshmukh [2010], they find that an uncoupled AGCM with only the observed SST changes specified in tropical ocean can reproduce the patterns of recent climate trends over several regions (e.g. North America, Greenland, Europe, and North Africa) more successfully compared to the state-of-the-art coupled AOGCMs with prescribed observed radiative forcing changes. Based on the studies discussed above, we take advantage of the current understanding of the climate system and the important role that tropical SSTs play in climate models. This knowledge provides us the possibility of conducting skillful forecasts of regional responses to tropical SST changes with acceptable errors so that we can provide decision makers with useful information to deal with variations in the climatic system and adopt suitable management strategies.

1.3 Objectives

Based on the discussion in previous sections, we would like to develop an efficient and robust tool for predicting regional changes of river flow and precipitation over river basins with respect to tropical anomaly SSTs patterns in the future. We realize that the regional climate changes over river basins may lead to severe impacts including extreme flooding events as well as water security, adaptation, and assessment of vulnerability over a target area. Therefore, by adopting the linear model developed in Li et al. (2012), we are able to estimate regional climate response
based on sensitivity information of any model variable (or calculated quantity from model data). The following sections of this research will build a framework to characterize the hydroclimate components of river basins and their resulting responses to tropical SST anomalies: We will first review data, methodology, and the linear model required for this study (Chapter 2). From existing model experiments, we estimate the sensitivity of regional climate responses to anomalous tropical SST patterns over 12 river basins. Then we examine the performance of the linear model over different river basins for the four seasons by first comparing the reconstructed values to atmospheric model output as a perfect model experiment and then comparing with observational data (Chapter 3).

We also would like to assess predictability of the linear model for hydrological component related to anomalous SST variability on seasonal timescale and river basin spatial scale. From the discussion above, we expect to understand more about the predictability of climate models and model behavior for predictions including how the complex interactions in the climate system are characterized in atmospheric climate models. As a second application in hydrology, we examine the predictability of the model by analyzing wetness and dryness tendency over target river basins (Chapter 3). Finally we present the conclusions (Chapter 4) and then discuss uncertainties of the method (Chapter 5). After assessing the validity of our method, we can investigate other various sources that might contribute to the overall uncertainty in climate predictions from a long-term view. By analyzing
the validity and uncertainty of the method based on different river basins at four seasons, we can also provide some perspective where climate modeling community can focus to improve climate models so that they can further reduce uncertainties related to predictions of regional climate change.

From a long-term perspective, we expect the method developed in this research can provide more reliable projections for studying regional climate impacts estimated for river basins. Estimating future seasonal or decadal changes in hydrological components over target river basins is one of our goals. Ultimately, we plan to incorporate our method for impacts research in other related fields such as agriculture, water use, and economics, because we realize that climate has become one of the primary determinants of those fields. Therefore, for both the public and climate research community, they can obtain an accurate and robust assessment of regional response to climate change from this research project and the policy makers can make assessment especially over those densely populated river basins that are highly affected by the regional climates.
This chapter presents the 12 river basins in the study (section 2.1), the experimental design (section 2.2), the models used (section 2.3), the data sets (section 2.4) and analysis method (section 2.5).

2.1 Description of River Basins

For this study, we focus on temperature and precipitation as the primary climate variables for hydrologic study recognizing that several additional variables are important. Different from previous works that focus on larger scale regions, we select 12 main river basins in the world for this study: Amazon and Parana River basins for South America; Niger, Lake Chad, Congo, Nile and Limpopo River basins for representing different parts of Africa; Indus, Ganges, Brahmaputra and Huang He River basins for Asia; Colorado and Mississippi River basins for North America (see Figure 2.1).
Figure 2.1: The 12 river basins studied in this research. Each colored region denotes a leaf-shaped river basin region based on digital elevation map (DEM) data.

As discussed in Barsugli and Sardeshmukh (2002), the changes of the hydrological cycle depend sensitively on prescribed pattern of regional tropical SST anomalies. Therefore, we focus on 12 river basins over certain regions where climate change might affect the regional hydrological cycle and by using sensitivity maps, we can diagnose and investigate that different ROIs are sensitive to which regions of SST anomaly patterns.

Regarding the SST anomaly (or perturbation) patterns, Barsugli et al. (2006) show that the spatial patterns of tropical SST trends have significant influence on
global mean temperature and precipitation and other studies discussed in Chapter 1 demonstrate the importance of tropical SST anomalies play in affecting climate system globally. In addition, Barsugli et al. (2006) emphasizes the necessity for more accurate predictions of SST trends over sensitive areas, and not just the overall amplitude of tropical ocean warming. In that way, uncertainties in global climate forecasts could be reduced. Therefore, in this project, we will extract tropical part of the global SST perturbation anomalies, which are generated as a forcing and the sensitivities of ROIs and those changes will be further explored. In other words, we can analyze teleconnection patterns of regional responses by using the SST anomalies over specific tropical regions.

For regional scale, the hydrological cycle of a river basin plays an important role in altering regional and global climate. One way to study and quantify the hydrological cycle of a particular catchment basin is using the concept of water balance, which is composed of various components. For regional climate system, the water-balance equation can be expressed as follows (Dingman, 2008):

\[
\frac{dS}{dt} = P - E - R
\]

(2.1)

where \( S \) is the soil water storage, \( P \) is precipitation, \( E \) is evaporation and \( R \) is runoff. However, obtaining \( R \) and \( P \) observations is relatively straightforward compared to \( S \) and \( E \). Therefore, we first focus on estimating temperature and precipitation over river basins in the study. Also, we are interested in the interan-
annual or longer time scale variations in regional water and energy balances over river basins, because the changes in circulation and precipitation pattern can ultimately be transmitted to affecting the streamflow of the river basin. These changes can also affect the atmospheric moisture transport from the region of the river basin to its adjacent regions.

Many studies have been done for investigating spatial and temporal variability of the water balance of several main river basins in the world. For example, Amazon River basin is the world’s longest, widest river and it also has different varying climatic and topographic characteristics along the river. Marengo (2005) found that the major differences exist in the characteristics of water balance and variability between the northern and southern parts of the basin. Their results showed that seasonality and interannual variability of the water balance vary across the basin. In addition, the anomalous components in the water balance over the northern part of Amazon region are associated with tropical Pacific interannual variability and ENSO. For example, during La Niña year (e.g. 1988 – 1989), the Amazon River basin has precipitation outweighing evaporation, which indicates the Amazon River basin is an atmospheric moisture sink at that time. Also, the large moisture transport from the tropical North Atlantic into tropical South America contributes to altering the water balance over Amazon River basin, as shown in Marengo (2005)’s study that moisture convergence occurs during austral spring (SON) and summer (DJF) between central Amazon region.
For Africa, the Niger River basin, located at west part of Africa, has a rainy summer and a dry winter associated with the movement of the Intertropical Convergence Zone (ITCZ) northward and southward of the equator. During JJASON period, the Saint Helena high-pressure area moves toward the north and initiates the monsoon season and brings humid and unstable maritime air and relatively cool temperatures for the Niger River basin; however, the DJFMAM period, the Saharan high-pressure zone brings hot, dry air and high temperatures. Also, the regional climate over Nile River basin is influenced by the summer monsoon from ITCZ and thus it also has a rainy summer and a dry winter. For Limpopo River basin in Southern Africa, it also has two distinct seasons – a wet season (NDJFMA) and a dry months (MJJASO) associated with the movement of ITCZ southward and northward respectively. The ocean also plays an important role in the regional climate over Limpopo River basin. The southward-flowing Mozambique current near the east brings warm water and humid air from the Equator to the region.

For the river basins in Southeast Asia (e.g. Indus, Ganges, Brahmaputra), they are fed by glacial and snow melting from the Tibetan Plateau and Himalayas as well as the following monsoon rainfall (Shaman et al., 2005; Kamal-Heikman et al., 2007). Storage component therefore also plays an important role in estimating the water balance over these river basins. The summer monsoon season is the main contributor for precipitation over these river basins in Southeast Asia.

For Colorado River basin in North America, the precipitation patterns there
have both winter and summer regimes (Hereford and Graham, 2002). Survey (2004) summarized that the precipitation in the headwater is even over the four seasons and they are mostly stored in snowpacks. For example, winter and spring frontal systems from the North Pacific Ocean provide the main source of moisture to Colorado River basin; however, it is strongly influenced by SST patterns over the tropical and North Pacific Oceans. In addition, during summer season, moist air can be transported to the region from the Gulf of Mexico, the Gulf of California, and the eastern Pacific, which is also known as North American monsoon. The impacts of SST over Pacific and Atlantic Ocean can also affect the streamflow over Mississippi River basin on continental U.S. (Tootle and Piechota, 2006).

2.1.1 River Basin Shape Data And Area-Averaged Hydrologic Variables

For this work, 12 major river basins over the world are selected as target regions in the study (Figure 2.1). To calculate areal mean response of the target river basins more precisely, we require digital elevation maps data to delineate shapes of drainage area of river basins (Differences can be visualized in Figure 2.2). Digital elevation maps data are provided as a set of shapes files that represent maps in vector or raster form (Band, 1986). These shape files are created from extracting topographic information, and map out the spatial structure of drainage basin area by using digital elevation models (DEM). The digital elevation maps data used
in this study are from World Resources Institute (WRI) Major Watersheds of the World Delineation, 2nd Edition and they have been widely used for regional studies (Jenness, 2007a,b). The shapefile data are comprised of 254 major river basins features around the world. Therefore, we use bilinear interpolation to manipulate our original model output data at T42 resolution which is approximately 2.8° on the Gaussian grid to 1024 by 2048 horizontal grids cells within a single model grid cell. After incorporating this technique, the calculations of area-averaged hydrologic variables are no longer based on coarse model grids. By using this higher resolution information, we improve the partitioning of hydrologic variables more precisely based on spatial variation and drainage area, which then includes a topographic-based partition of different watersheds.
Figure 2.2: The illustrative figures for visualizing the difference between applying DEM data to calculating areal averaged arbitrary data within the leaf-shaped river basin region (b) and without the DEM data but with original model grids (a). Figures shown here are for river basins over Africa with arbitrary precipitation data from model output.
2.2 Model Description and Methods

2.2.1 Regional Climate Sensitivity

To examine teleconnection information in this study, we estimate the linear dependence of climate variables on changes in local tropical SSTs. We refer to these as sensitivities of regional climate to tropical SST anomalies. The initial investigation of sensitivity of atmospheric response to anomalous SST patterns over ocean basins was done by Barsugli and Sardeshmukh (2002). In their work, they performed a large ensemble of simulations with an atmospheric general circulation model (GCM) with an array of localized SST anomaly patches spanning the tropical Indian and Pacific Ocean basins. (We note that they did not include the tropical Atlantic basin.) (Barsugli and Sardeshmukh, 2002). According to the study, analyzing the responses to individual patches can determine the locations where SST anomalies are effective at forcing a climatic response (i.e. precipitation) in some remote target locations around the globe. Therefore, a method has been provided to determine the sensitivity of climate change to tropical SSTs by simulating a large set of “patch experiments” (Barsugli and Sardeshmukh, 2002; Barsugli et al., 2006) where the patterns are defined to represent typical spatial variations in tropical SST patterns. The sensitivity of large-scale response at some regions of interest (ROIs) to localized SST anomalies can also be quantified from this method. Hence, the sensitivity is defined as a change in a given variable aver-
aged over a certain ROI divided by the change in the areal averaged SST anomaly at the given location. In addition, by moving the SST anomaly patch to different locations, the sensitivity for a ROI can be mapped out across the tropics. The spatial scales of SST anomaly patches in Barsugli and Sardeshmukh (2002) and Barsugli et al. (2006) are indicated in Figure 2.3 (a) as adapted from Li et al. (2012).

![Figure 2.3:](image)

**Figure 2.3:** (a) SST anomaly patches used in Barsugli and Sardeshmukh (2002) and Barsugli et al. (2006). Two examples (b)(c) of perturbed SST fields over the tropical region used in Li et al. (2012) (adapted from Li et al. (2012)).

Distinguished from Barsugli and Sardeshmukh (2002), which estimated sensitivity to tropical SST anomalies by setting a single patch of SST perturbation
in a given location for individual runs, Li et al. (2012) proposed an alternative method to assess sensitivity by applying a set of random SST perturbations over the entire tropical ocean (see Figure 2.3 (b) and (c)) for each simulation in NCAR’s (National Center for Atmospheric Research) CAM v3.1 model (Community Atmospheric Model). As the assessment of sensitivity of regional climate change requires a large number of ensemble runs to obtain reliable results, Li et al. (2012) introduced the Random Perturbation Method (RPM) which specifies an ensemble of randomly perturbed tropical SST patterns for the AGCM and thus this increases computational efficiency. According to their study, there is a strong similarity between response of the AGCM to the patch and RPM SST forcings and hence sensitivity patterns for different variables over several regions are similar. Li et al. (2012) concluded that the patch method is a more direct way to detect teleconnection response, however, the RPM provides similar features using a 200-member ensemble. Therefore, different options exist to explore sensitivity of large-scale seasonal response to perturbed SST patches. One is setting a set of single fixed patches and running individual ensembles for each (known as the Patch Method as introduced in Barsugli and Sardeshmukh (2002)). The other is setting random patches across the tropical ocean basins and running a single ensemble to estimate sensitivity to all perturbed SST regions (known as RPM). This study will use the RPM and examine its validity of further applications.
2.2.2 Description of the Random Perturbation Method

As discussed in section 2.2.1, we require estimates of regional climate sensitivity responding to SST anomaly patterns. These estimates are calculated using results from AGCM simulation experiments using the National Center for Atmospheric Research (NCAR) Community Atmospheric Model (CAM) version 3.1 (Collins et al., 2004). These experiments and the model setup are described here. The primary results for this study are obtained from model simulations from Li et al. (2012). The model used in that study is also the CAM 3.1 from NCAR with T42 resolution (128 by 64 horizontal grids cells, which is also approximately 2.8 degree resolution). The model configuration includes the Community Land Surface Model (CLM) as an interactive land surface component to include land process feedbacks (The model data used for calculation courtesy of Dr. Wei Li). The experimental design for RPM simulations requires adding perturbed SST fields to a monthly climatological SST and sea ice data set, given by the HadOIBl data, in order to conduct sensitivity experiments (McCaa et al., 2004).

2.2.3 Description of AMIP-style simulations

For this study, we use AMIP-style simulations to evaluate performance of the linear model estimated from CAM 3.1. The AMIP-style experiments are simple by design and discussed below. This model configuration is the AGCM forced by historical SST fields that enables us to focus merely on atmospheric model without complex-
ity of ocean-atmosphere feedbacks in the climate system. Therefore, in this study we used 15 AMIP-style runs for comparing the results from CAM 3.1, and we define this kind of AMIP-style simulations as “AMIP runs” throughout the thesis. The Atmospheric Model Intercomparison Project (AMIP) (Gates et al., 1999) was designed to examine the systematic errors from atmospheric climate models and has since been used for many investigations into atmospheric model behavior. We adopt the protocol of AMIP that specifies realistic boundary conditions for the 1948 – 2000 period (e.g. AMIP runs (Deser et al., 2006)). The CAM 3.1 simulates climate by using observed monthly-averaged distributions of SST and sea ice from 1948 to 2000 as boundary conditions. With complete variable fields saved for diagnostic research, the AMIP studies established a standard experimental protocol for atmospheric general circulation models (AGCMs). It provides a community-based framework for climate modeling validation and comparisons. This framework enables scientists to analyze AGCMs in a systematic fashion and examine validation of model performance.

2.2.4 Experimental Design of Random Perturbation

Method

As section 2.2.2 mentioned, we use the NCAR CAM3.1 with T42 resolution to perform ensemble simulations. The model set up for adopting the random perturbation method (RPM) is that we use randomly perturbed SST fields to force
the AGCM and estimate the sensitivity of regional climate variables to tropical SST anomalies at seasonal scales. The essence of RPM is that one can randomly perturb climatological SST field with spatially coherent anomalies and estimates anomalous response with respect to climatological equilibrium state. After obtaining the model output, we estimate sensitivity when incorporating SST anomalies in RPM fields. The estimated sensitivity values can be mapped out onto the tropical SST locations to visualize as sensitivity maps (see Figure 3.1 in Chapter 3). Then we can reconstruct regional response based on the sensitivity information obtained before. Finally, we will compare linear reconstruction of variables over 12 river basins to AMIP runs output as well as observational data.

2.2.5 Random Perturbation Method (RPM)

In this study, we follow the random perturbation method (RPM) developed by Li et al. (2012) that is a more efficient way for calculating sensitivities of regional climate than the method used in Barsugli and Sardeshmukh (2002). Barsugli and Sardeshmukh (2002) used a set of individual SST anomaly patterns and then estimated sensitivities by moving the patches systematically around the tropics. We first generate a set of random SST perturbation fields from a white-noise uniform distribution over the interval from -2K to 2K (see Figure 2.4 (b)). The perturbed SST anomaly range includes those used in Barsugli’s work (Barsugli and Sardeshmukh, 2002; Barsugli et al., 2006) over the entire tropical ocean and they are added
to climatological SST fields. Based on previous research (Barsugli and Sardeshmukh, 2002; Barsugli et al., 2006), because the mean state of atmospheric response to tropical anomalous SST forcing can be approximately regarded as a linear process, we can estimate sensitivity in this similar fashion.

According to Li et al. (2012), a $16 \times 16$ random matrix of SST anomaly values are randomly generated across the entire globe with equal spacing in longitude (22.5 degrees resolution) and latitude (11.25 degrees resolution) (see Figure 2.4 (a)). The SST anomalies are interpolated to the AGCM model grid resolution (i.e. T42 resolution, which is a $128 \times 64$ grid) by using bilinear interpolation. As mentioned above, each point on the $16 \times 16$ grid is randomly determined from a uniform distribution within the range of -2K to 2K (maximum temperature is 2 K). In other words, the perturbations on the $16 \times 16$ matrix have random magnitude and they are uncorrelated in space and between ensemble members. After the bilinear interpolation, the anomalies on the T42 grid have a decorrelation length defined by the $16 \times 16$ grid. An ensemble of SST perturbation fields is then generated randomly with 1000 members and added to model climatological SST field as a forcing for the model ensemble simulations. The model is forced with the updated SST field and a branch run is conducted starting from the 10th year of a 160-year control simulation since that allows a 9-year spin-up for control run to reach an equilibrium state. Additionally, to consider uncertainty in initial conditions, 200 branch runs are conducted from different starting points and run 20 months for
each set of perturbation field. The model output from 9th – 20th month is extracted to calculate seasonal mean responses.
Figure 2.4: Examples of SST perturbation fields over the entire globe (a) and tropical region (b). The range of SST perturbations is from -2K to +2K. (Courtesy of Dr. Li at Department of Meteorology, The Pennsylvania State University)
2.2.6 Calculating Regional Climate Sensitivity

We will first discuss how to calculate the sensitivities shown in Figure 2.5 and its background knowledge and then return to discuss the maps. According to Barsugli’s work (2002 and 2006), they use several GCM output to determine the “Green’s function” for atmospheric response to anomalous SST fields in the tropics.

As mentioned in Chapter 1, the underlying assumption for applying this concept is that the seasonal mean atmospheric response to any large-scale SST pattern can be expressed as a linear combination of the multiple responses to localized SST field. This concept has been widely used in statistical mechanics and this Green’s function approach has also been applied to many climate-related research (e.g. Simmons et al. (1983); Branstator (1985); Newman and Sardeshmukh (1998)).

Even though the governing equations in the full GCM are nonlinear, temporally and spatially averaged variables can be described by linear dynamics through this conceptual simplification. We apply the Green’s function that represents seasonal climate anomalous response $R(x)$ to anomalous SST $T(x)$ at location $x'$ as follows:

$$R(x) = \int_{A'} G(x, x')T(x')dA' + \varepsilon(x) \quad (2.2)$$

where $dA'$ indicates the area integral over $x'$ and residual $\varepsilon(x)$ includes nonlinearities coming from internal variability of the atmosphere and it is dominated by Gaussian random variable. The formula can also be rewritten in discretized form
as follows:

\[ R_j = \sum_k G_{jk} T_k A_k + \varepsilon_j \]  

(2.3)

Here \( G_{jk} \) is the matrix form of the Green’s function of response at location \( j \) to anomalous SST at location \( k \). Therefore, we may now treat the regional ensemble-mean response to an individual arbitrary SST anomaly field as a sum of the individual responses. Furthermore, the approximate Green’s function can contribute for sensitivity analysis by applying a statistically based smoothed operator to the individual responses and increase its statistical significance by trading off spatial resolution of sensitivities. Based on the knowledge above, several steps are necessary to generate meaningful sensitivity maps (see also Barsugli and Sardeshmukh (2002)). First, we compute the linear response to SST for each patch as the ensemble anomalous mean responses to anomaly forcing so that results (sensitivities) can relate a large set of tropical SST perturbations to regional climate change response. The advantage of this method is that it can map out the relationship between arbitrary spatial-scale SST anomalies and arbitrary responses of any target river basin over the tropics. Actually, this larger relationship is essentially characterized by the GTO (so-called sensitivity), from which more specific metrics of regional climate response of a given ROI can be calculated spatially. From equation 2.2, the analytical framework is centered on the mathematical relationship with the operator \( (G) \) linking tropical anomalous SST forcings and regional-scale climate response around the globe. Because the timescales of oceanic variability are typi-
cally longer than intrinsic atmospheric timescales, the decadal scale variability of atmospheric and regional climate response can be treated as quasi-steady. Therefore, the anomalous response vector \((X)\) to anomalous SST forcing vector \((F)\) can be approximated by a multilinear relationship (more detail discussed in Barsugli et al. (2006)):

\[
X \approx G \cdot F + \varepsilon
\]  

where \(\varepsilon\) allows for a random error due to intrinsic atmospheric variability. If we further construct a scalar climate response index \((R)\) from the full state vector \(X\); for example, \(R\) could be the anomalous precipitation, averaged over a region of interest, we can write:

\[
R \approx K \cdot F + \varepsilon
\]  

The vector \(K\) is the sensitivity of the response to the different locations of anomalous SST forcings. As discussed before, the sensitivities can be mapped geographically to generate a “sensitivity map”, which is a convenient way to visualize the part of the full operator (anomalous SSTs over the ocean) that is relevant to a certain geographical region (river basin).

2.2.7 Maps of Regional Climate Sensitivity

After calculating sensitivity, we can map it out by plotting a map of the regional climate sensitivity (Figure 2.5). A sensitivity map is a contour map of regional
climate variable responses to the SST anomaly field and the response is scaled by area-averaged magnitude of the SST anomalies. We can diagnose and investigate that different ROIs are sensitive to which SST anomalies region through sensitivity map and detect which part of the SST fields might affect regional hydrological cycle over certain river basin. While Barsugli et al. (2006) primarily examine global-scale response, Barsugli and Sardeshmukh (2002) include global as well as multiple regional areas in their analysis. Based on this, in this study, we focus on the sensitivities of regional climate response of 12 river basins to random SST anomaly patterns with RPM, which is also more computationally efficient but still shows the ability to estimate sensitivities. To provide more understanding about sensitivity map, the results of sensitivity maps for both temperature and precipitation over 12 river basins will be shown and discussed in Chapter 3.

In this study, as mentioned in Chapter 1 (section 1.2.1), we only include the SST perturbations from the RPM fields over the Tropical Ocean rather than global perturbed SST fields (Figure 2.4 (a)) based on the following reasons: First, preliminary results show that using perturbed SST fields over the tropical ocean highlighted the significant role that the tropics play in estimating regional sensitivity information as compared to the global case, as shown by similar results (Figure 2.5). To compare the results in Figure 2.5, we extract the perturbed SST field from the RPM over the tropical ocean (30 degree south to 30 degree north) from the global domain. To avoid a sharp decrease at the 30° boundaries, a tapering
between 20 degree to 30 degree (both South and North) is applied to ensure a smooth transition in the SST perturbation field (see Figure 2.4 (b)). To calculate the sensitivity values, we link SST anomaly patches and the entire response over the target river basins through regression coefficients that reflect the global teleconnection relation between them. After that, a matrix form of sensitivity information can be defined as a global teleconnection operator (GTO).
Figure 2.5: Sensitivity maps created by applying tropical SST perturbation fields (a) and global SST perturbation field (b). The sensitivity patterns of both are similar and significant at the tropics. (Courtesy of Dr. Li at Department of Meteorology, The Pennsylvania State University)
2.2.8 Reconstruction

After producing sensitivity maps, we now validate the performance of how a regional climate anomaly can be predicted using a linear regression model using tropical SST anomalies. Based on the linear reconstruction method used in Barsugli’s study (Barsugli and Sardeshmukh, 2002; Barsugli et al., 2006) and Li et al. (2012), we multiply our sensitivity map for each river basin from the RPM by weighted historical SST anomaly fields over the last half-century from 1950 – 2000 to estimate the reconstructed linear component of regional climate anomaly. The formula is as follows (Li et al., 2012):

\[ R_j(t) = \sum_{k=1}^{N} \frac{\Delta SST(x_k, t) \Delta SST(x_k)}{2\beta} K_{jk} A \]

(2.6)

In this formula, \( \Delta SST(x_k, t) \) is historical SST anomaly from HadOIB1 during 1950 – 2000 at location \( x_k \), whereas \( \Delta SST(x_k) \) is anomalous SST field used in the patch method and serves as a weighting function here. \( K_{jk} \) is the sensitivity of interested river basin region \( j \) to SST anomaly location grid \( k \), and \( A \) is averaged grid-box area. \( N \) is the total ocean grid in the model, and here we set \( \beta \approx 10 \) for river-basin scale region but it actually varies from 8 – 56 for reconstruction of temperature at 850hPa and 8 – 48 for precipitation according to the analysis from Li et al. (2012). \( \beta \) is a constant related to the decorrelation length scales of the SST forcing and regional response based on atmospheric dynamics. Because we use correlation
results in this study, $\beta$ will not affect the interpretations. After we reconstruct the anomalous responses ($R_{\text{linear}}$), they will be compared to ensemble mean anomalies ($R_{\text{full}}$) from the ensemble of runs by the same GCM with the full pattern of historical SSTs from 1950 – 2000 applied. Also, the results from observed-SST forced AMIP run will be compared to the results of reconstruction. When doing reconstruction, several time series plots of $R_{\text{linear}}$ and $R_{\text{full}}$ of interested quantities are created and correlations are calculated. If there are high correlations between time series, it shows that the linear reconstruction approach successfully reproduces the annual GCM response to historical SST anomalies well (Barsugli et al., 2006).

### 2.3 Observational Precipitation Data

We use two observational data sets for climatological precipitation in this study. The first precipitation data set used for comparing reconstruction results in the study is from the Global Precipitation Climatology Project (GPCP). It is developed by the World Climate Research Program (WCRP) and it combines the precipitation information from several sources into a single merged product, utilizing the strengths of each data type. For example, the microwave component estimates are based on polar satellite. The infrared (IR) component estimates are used from geostationary satellites developed from different countries and institutes. The station gauge data are analyzed by the Global Precipitation Climatology Centre (GPCC) of the Deutscher Wetterdienst. The GPCP has been dedicated to devel-
oping an analysis procedure for merging various data sources together to produce
global gridded precipitation data. We use GPCP Version 2.2 Combined Precipita-
tion Data Set in this study and operational procedure is available in Adler et al. (2003) and Huffman et al. (2009). This data set covers the period from January 1979 through the present (2012). The version we use is based on gridded analysis from gauge measurements and satellite estimates of rainfall with a 2.5° × 2.5° resolution. (Acknowledgement: The GPCP Precipitation data is provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, and it is available from their website at http://www.esrl.noaa.gov/psd/)

A second observed precipitation data set is used for constructing Standardized Precipitation Index (SPI, will be discussed more in Chapter 3) in this study. It is the 50-Year VASClimO Data Set 1951 to 2000 (V1.1) with 2.5° × 2.5° resolution. The data is developed from quality-controlled data from 9343 stations and it is temporally optimized for homogeneity and been widely used in climate variability studies. VASClimO stands for Variability Analysis of Surface Climate Observations and it is a joint climate research project from the German Weather Service (Global Precipitation Climatology Centre/GPCC). This product is also used as a land-surface reference for the GPCP Satellite-Gauge Combination as previously mentioned and includes gauge-bias corrections (Beck et al., 2005).
RESULTS AND DISCUSSION

In this chapter, we present the results first by examining the dependence of climate information to changes in tropical SST anomaly patterns. Second, we evaluate the approach by comparing the linear reconstructed results with both results from AMIP runs and observational data. As a third test, we apply our method to identify wetness and dryness tendency over the 12 river basins we selected.

3.1 Global Teleconnection Sensitivity Maps

We first present the sensitivity of regional climate response estimated over the river basins to tropical SST anomaly ($dR/dSST$). To represent the large-scale response, we show the sensitivity of basin-averaged temperature at 850 hPa and precipitation (unit: $mm/day$) for a subset of our river basins from the linear model (Figure 3.1). As discussed in Chapter 2, sensitivity maps are shown as a contour map of the estimated sensitivity ($K = dR/dSST$), which is the same $K$ as shown in Equation
2.5 in Chapter 2). The following river basins are selected across different continents including: Amazon River basin from South America, Niger River basin from West Africa, Congo River basin from Central Africa, Nile River basin from East Africa, Limpopo River basin from South Africa, Ganges and Brahmaputra River basins from South-East Asia and Mississippi River basin from North America. These are representative of the sensitivity maps for other river basins on the respective continents over the world.
Figure 3.1: Regional sensitivity maps of temperature at 850hPa (left panel) and precipitation (right panel) for the respective river basins. The maps are shown for (a) Amazon River basin, (b) Parana River basin, (c) Niger River basin, (d) Lake Chad River basin, (e) Congo River basin, (f) Nile River basin, (g) Limpopo River basin, (h) Colorado River basin, (i) Mississippi River basin, (j) Indus River basin, (k) Ganges and Brahmaputra River basins, (l) Huang He River basin. Shaded regions indicate where the sensitivity signal is significant by using a two-tailed t-test at 20% significance level. (Units: $K \cdot km^2 \cdot 10^9$ for T850 and $mm/day$ per $K \cdot km^2 \cdot 10^9$ for precipitation.)
To provide a more intuitive understanding about sensitivity maps, we discuss briefly the sensitivity maps for both temperature and precipitation over Amazon River basin as an example (Figure 3.1 (a)). First, the positive values (shown in red) mean that a positive change in SST implies a positive change in the basin-average T850 or precipitation over Amazon River basin. Second, we observe opposite sensitivity patterns between T850 and precipitation at the same location in tropical ocean. One interesting feature is that the sensitivity information mostly has the strongest magnitude near the location where the river basin is situated. For example, the maximum sensitivity of both T850 and precipitation over the Amazon River basin is shown in the nearby tropical part of Atlantic Ocean. Similar descriptions are seen for other river basins in Africa, which having strong sensitivity to SST changes over the Indian Ocean. For specific patterns for the Amazon River basin, for T850, the positive sensitivities extend in a broad swath over tropical part of the Pacific and Indian Oceans in general, and also over the Caribbean Sea in JJA and SON. It denotes that the warming of SST over those oceans with positive sensitivity values will lead to temperature increases over the Amazon River basin. Negative sensitivities are mostly located over the tropical part of the Atlantic Ocean, which means that the warming of SST over the Atlantic Ocean will result in decreasing of temperature at Amazon River basin. For precipitation, negative sensitivities over the tropical part of Pacific Ocean (especially west side) and Indian Ocean indicate that warm SST anomalies can cause less precipitation
over Amazon River basin. However, positive sensitivity information in the tropical Atlantic Ocean brings wet anomaly. Note that sensitivities shown above are seasonal mean instead of annual-mean response to long-term trends in SST so that the seasonal cycle in climate response can be illustrated.

As for other river basins such as Parana (Figure 3.1 (b)), Indus (Figure 3.1 (j)), Colorado (Figure 3.1 (h)) and Huang He (Figure 3.1 (l)), we observe that those located within the same continent show similar patterns on the sensitivity maps of temperature and precipitation due to their geographical locations. For example, river basins such as Niger (Figure 3.1 (c)), Lake Chad (Figure 3.1 (d)), Congo (Figure 3.1 (e)) and Nile (Figure 3.1 (f)) display fairly similar sensitivity patterns. Specifically, the dipole in the Indian Ocean for precipitation and the sensitivity information is strongest during the SON season in general for all basins. Compared to other studies for East Africa climate, Black (2005) and Ummenhofer et al. (2009) have illustrated the relationship between the Indian Ocean Dipole (IOD, a coupled ocean-atmosphere phenomenon occurring in the equatorial Indian Ocean and it affects the climate of countries around the Indian Ocean basin. A positive IOD period is defined as anomalous cooling SSTs over the tropical eastern Indian Ocean and anomalous warming SSTs over the tropical western Indian Ocean (Saji et al., 1999), the El Niño Southern Oscillation (ENSO) and SON rainfall in East Africa by using observational data. The SST patterns also show that East African rainfall (peak rainfall during SOND) is related to warming in the Pacific.
and Western Indian Oceans and cooling in the Eastern Indian Ocean, which is consistent with our sensitivity results. However, for Limpopo River basin at South Africa (Figure 3.1(g)), the sensitivity pattern shows different features compared to other river basins over Africa in the present study. The positive sensitivities for precipitation reach their maximum in DJF and SON over tropical West Pacific Ocean as well as the tropical Atlantic Ocean. Evident negative sensitivities are situated over the Indian Ocean throughout the year except for JJA which shows much weaker negative signals.

The Mississippi and Colorado River basins over North America represent a continental region in the extratropics and also show similar sensitivity signals. The sensitivity patterns of precipitation for the Mississippi River basin have positive anomalies over tropical central and east Pacific Ocean and slightly negative patterns over the Atlantic Ocean. The patterns illustrated above for Mississippi River basin also correspond to the observation and it also can potentially be explained by the impact of the Caribbean Low-Level Jet (CCLJ) on precipitation over central United States. CCLJ is characterized by a maximum of easterly zonal wind at 925 hPa over the Caribbean region (Amador, 1998; Amador et al., 2000). CCLJ anomalies are inversely correlated to the Caribbean SST anomalies as well as tropical North Atlantic (TNA) anomalous SSTs and CCLJ is largely influenced by variability of the North Atlantic subtropical high (NASH). Warm TNA SSTs or Caribbean SST anomalies can increase local atmospheric convection and therefore
resulting in low sea level pressure (SLP) and this weakens NASH which carries moisture from the ocean to the central United States by meridional wind and thus it reduces precipitation over the Mississippi River basin. CLLJ generally exists in the whole year, having two maximum in summer and winter. The negative sensitivity results of precipitation shown in the TNA and Caribbean region (except JJA) provide a potential illustration for dynamical mechanisms associated with CLLJ. This potentially explains when warming occurs over TNA and Caribbean region, the increasing local atmospheric convection reduces strength of NASH as well as CLLJ, and the moisture can no longer be transported as much as it could be before. Also, we can observe that a competition exists between the influences from the Pacific and the Atlantic Oceans on North American precipitation. This has been demonstrated in previous studies (Giannini et al., 2001; Wang, 2007) and it leads to multiple impacts by teleconnections on the Mississippi River basin, resulting in more variability in precipitation.

Indus, Ganges and Brahmaputra River basins also have similar sensitivity patterns for precipitation but with different magnitude across the seasons. The Indus River basin has strongest dipoles over Indian Ocean in JJA and SON; however, Ganges and Brahmaputra River basins have it in MAM and the dipole disappears in DJF and it is replaced by positive sensitivity information. The Huang He River basin shows slightly different sensitivity information over Indian Ocean compared to Indus, Ganges and Brahmaputra River basins with different dipole pattern oc-
curring in JJA and more significant sensitivity information showing in the west and central Pacific Ocean; however, the sensitivity of precipitation over Huang He has significant negative values over tropical Pacific Ocean in DJF and MAM while it reaches maximum values during JJA and SON over the tropical west Pacific Ocean accompanied with positive signals at east Pacific Ocean.

Overall, East Africa and Southeast Asia are two regions strongly influenced by monsoon activity. The sensitivity plots reveal a common pattern that those regions are sensitive to the SST anomaly over the Indian Ocean and the west Pacific Ocean. Also, the dipoles between the Indian Ocean and west Pacific Ocean are observed in the sensitivity maps of winter temperature over river basins in North America and winter and summer precipitation over East Africa and Southeast Asia. Corresponding to other regional climate studies of these river basins, the dipoles indicate that SST patterns usually will trigger and alter local circulations over these regions. Therefore, from sensitivity maps, we can identify that the SST variability can be viewed as a cause for variability in both circulations and rainfall. Although there is still substantial variability existing over several river basins (e.g. Limpopo River basin (Reason et al., 2005), Ganges and Brahmaputra River basins (Jian et al., 2009) etc.), we can still examine the sensitivity of different river basins to certain parts of the SST anomalies. The sensitivity map can be further regarded as a measure to quantify the regional climate change to anomalous SST patterns, because it shows not only the correlation between tropical forcing and the response
but also its amplitude.

As a final comment on the sensitivity maps, we note two important features. First, the information is scaled and independent of strength of the SST forcing. This implies that the actual magnitudes of SST variability are required to assess the net changes of the regional climate. Second, the information depends on the background climatological SST applied from different seasons. This allows us to observe seasonal changes of the responses for different locations in the tropical ocean. This also helps us understand the importance of seasonal time scale of regional climate sensitivity over river basins.

### 3.2 Linear Reconstruction of Climate Change over River Basins

After calculating the sensitivities of different river basins and observing their patterns shown on the maps, we can now use this information to reconstruct the regional anomalous responses over twelve river basins when given historical patterns of SST anomalies (see Equation 2.6 in Chapter 2). We multiply the sensitivity by historical SST anomalies to obtain reconstruction values of the seasonal climate changes for each basin. Then we compare these reconstructed values to output from AMIP simulation first. Because AMIP is a standard experimental protocol for AGCMs, it is suitable to evaluate performance of CAM 3.1 as used in the study.
3.2.1 Comparison of Linear Reconstruction with AMIP results

Similar to the analysis done by previous studies (Barsugli and Sardeshmukh, 2002; Li et al., 2012), we correlate the reconstructed response anomaly with the result from ensemble mean from the full CAM model runs forced by the observed SST during 1948 – 2000 to evaluate the performance of linear model. Therefore, we calculate correlation coefficient of the reconstructed response and the AMIP ensemble means during 1950 – 2000 for 12 river basins from RPM. The ensemble average of 15 AMIP runs is used for a correlation and the critical value of the correlation coefficient for n = 51 is 0.27 at a significance level of 5% because we have 51 years (Miller (1994), Table 8.2).

The correlation coefficients of reconstructed values and AMIP results for T850 and precipitation and some selected time series plots are shown as follows (Figure 3.2).
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<th>Season</th>
<th>Region</th>
<th>Precip</th>
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</tr>
<tr>
<td>Nile</td>
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(e) Congo

(f) Nile
Figure 3.2: Time series plots of reconstruction values (solid line) and AMIP run results (dash line) of T850(K) and precipitation (mm/day) for 12 river basins. (a) Amazon River basin, (b) Parana River basin, (c) Niger River basin, (d) Lake Chad River basin, (e) Congo River basin, (f) Nile River basin, (g) Limpopo River basin, (h) Indus River basin, (i) Ganges and Brahmaputra River basins, (j) Huang He River basin, (k) Colorado River basin, (l) Mississippi River basin.
Reconstruction Correlation Coefficient

AMIP v.s. REC

For 1yr, Critical Value=0.27, values more than that marked in red

<table>
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<th>Temperature at 850 hPa</th>
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<th>Precipitation</th>
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<td>-0.02</td>
<td>0.08</td>
<td>0.50</td>
</tr>
<tr>
<td>Limpopo</td>
<td>0.81</td>
<td>0.64</td>
<td>0.48</td>
<td>0.79</td>
</tr>
<tr>
<td>Huang He</td>
<td>0.57</td>
<td>0.62</td>
<td>0.51</td>
<td>0.38</td>
</tr>
</tbody>
</table>

Table 3.1: The correlation coefficients for seasonal means of reconstructed values and AMIP results for temperature at 850hPa (left) and precipitation (right) during 1950 – 2000 for 4 seasons over 12 river basins.

The results show that correlations between the linearly reconstructed response and the full atmospheric model response from AMIP runs are statistically significant for most of the river basins across the seasons (e.g. For T850, 11 out of 12 in DJF; 9 out of 12 in JJA; 11 out of 12 in SON; 11 out of 12 in MAM. For precipitation, 11 out of 12 in DJF; 11 out of 12 in JJA; 10 out of 12 in SON; 9 out of 12 in MAM). In other words, the regional climate changes over different river basins are reconstructed well by the linear regression of anomalous SST, and it is probably due to the smoothed noisy signal within large-scale averaged historical SST record (Li et al., 2012). River basins in tropical regions generally have better reconstructed results when compared with AMIP runs than those in the extratropical regions. The temperature response shows slightly better correlations than the precipitation owing to the signal being a less noisy at regional scales.
3.2.2 Comparison of Linear Reconstruction with Observational Data

After comparing the reconstruction results to ensemble-mean AMIP results, we compare the results to observational data to examine whether the linear approximation method can assess climate variability and change forced by anomalous SST patterns that impacts the river basins.

<table>
<thead>
<tr>
<th>Season</th>
<th>Running Mean</th>
<th>JJA</th>
<th>SON</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1yr(50)</td>
<td>5yr(46)</td>
<td>10yr(41)</td>
</tr>
<tr>
<td></td>
<td>AMIP</td>
<td>Obs</td>
<td>AMIP</td>
</tr>
<tr>
<td>Amazon</td>
<td>0.99</td>
<td>0.83</td>
<td>-0.14</td>
</tr>
<tr>
<td>Parana</td>
<td>0.99</td>
<td>0.87</td>
<td>0.01</td>
</tr>
<tr>
<td>Niger</td>
<td>0.49</td>
<td>0.50</td>
<td>0.47</td>
</tr>
<tr>
<td>Lake Chad</td>
<td>0.65</td>
<td>0.16</td>
<td>0.11</td>
</tr>
<tr>
<td>Congo</td>
<td>0.50</td>
<td>0.05</td>
<td>0.53</td>
</tr>
<tr>
<td>Nile</td>
<td>0.29</td>
<td>0.28</td>
<td>0.19</td>
</tr>
<tr>
<td>India</td>
<td>0.51</td>
<td>-0.02</td>
<td>-0.04</td>
</tr>
<tr>
<td>Colorado</td>
<td>0.45</td>
<td>0.24</td>
<td>0.70</td>
</tr>
<tr>
<td>Ganges&amp;Brahmaputra</td>
<td>0.37</td>
<td>0.38</td>
<td>0.58</td>
</tr>
<tr>
<td>Mississippi</td>
<td>0.37</td>
<td>-0.12</td>
<td>0.70</td>
</tr>
<tr>
<td>Limpopo</td>
<td>0.64</td>
<td>-0.11</td>
<td>0.84</td>
</tr>
<tr>
<td>Huang He</td>
<td>0.58</td>
<td>0.53</td>
<td>0.74</td>
</tr>
</tbody>
</table>

Table 3.2: The correlation coefficients of reconstructed values vs. AMIP results and observational data for precipitation with four seasons (DJF, MAM, JJA, SON) and 3 different averaging periods (1-year, 5-year, and 10-year running mean). Different colors indicate different critical values at the significance level of 5% according to the years in different running means.
(a) Amazon

1yr

DJF MAM JJA SON
(c) Niger

SON

JJA

MAM

DJF

1yr
5yr
10yr
(d) Lake Chad

DJF
MAM
JJA
SON

1yr
5yr
10yr

AMP
recognition

AMP
recognition

AMP
recognition

AMP
recognition

(f) Nile

SON

JJA

MAM

DJF

1yr

5yr

10yr
(g) Limpopo

DJF  |  MAM  |  JJA  |  SON
---|---|---|---
1yr | | | |
5yr | | | |
10yr | | | |
(j) Ganges & Brahmaputra

SON

JJA

MAM

DJF

1yr

5yr

10yr
(k) Colorado

DJF

MAM

JJA

SON

1yr

5yr

10yr
Figure 3.3: Scatterplots of reconstruction values, AMIP run results and observational values of precipitation (mm/day) for selected river basins and seasons (Selected results at a significance level of 5% marked in pink boxes). (a) Amazon River basin, (b) Parana River basin, (c) Niger River basin, (d) Lake Chad River basin, (e) Congo River basin, (f) Nile River basin, (g) Limpopo River basin, (h) Huang He River basin, (i) Indus River basin, (j) Ganges and Brahmaputra River basins, (k) Colorado River basin, (l) Mississippi River basin.
The reason for applying a running average is to smooth out short-term fluctuations and highlight longer-term trends in time series data. In our study, 5-year and 10-year running mean smooth out interannual variability and show higher correlations between reconstruction results and observed data or AMIP results. This will also reduce the degrees of freedom and affect the significance level.

From Table 3.2 and Figure 3.3, we can conclude the following statements:

1. Overall, reconstructed results of the linear method have better correlation with AMIP results compared to observational results, which means that our linear model can capture the features that non-linear model from AMIP-style simulations can produce and this also demonstrates the validity of the linear relationship.

2. In general, results with 5-year and 10-year running mean show better significance than those with no running mean applied except for SON season. This indicates that our method can detect decadal (or 5-year) variability better than year-to-year changes, and therefore our linear model shows more potential predictability for longer timescale changes.

3. 5-year running mean also shows high significance (especially for AMIP results and for both AMIP and observational results in MAM) except for observed data during SON and JJA season.
The performance of the linear model varies from different seasons and different region as Table 3.2 shows. The reconstructed precipitation results of Niger, Nile River basin show overall statistically significant correlation with AMIP and observations for all seasons at different timescales except for SON. For river basins in South America, the reconstructed precipitation results correlate better with AMIP and observations during MAM and JJA seasons. Although there are several features or physical mechanisms that our method or model cannot capture (will be discussed in Chapter 5), we still conclude that the linear method can detect and assess decadal variations of regional climate variables with respect to anomalous SST patterns. The inconsistency between reconstructed values and observational data cannot be resolved thoroughly in shorter time and it might be caused by noise and nonlinearity in climate system. For some regions having small linear signal, the noise might overwhelm the linear response. As Li et al. (2012) suggested, because the approach we used is based on the larger scale dynamics and thermodynamics of the atmosphere. For smaller spatial scale over river basins, take precipitation as an example, the local moisture that evaporating from land surfaces is not only a source for later precipitation, it might also alter the local thermodynamic structure of the atmosphere via changes in the circulation and rainfall. Therefore, those nonlinearities in the response over river basins to anomalous SSTs may be dominant over the linear signal despite using large ensemble sizes.
3.3 Application: Drought Index (SPI)

After evaluating the linear method by comparing reconstructed values with AMIP results and observational data for T850 and precipitation variables, we next apply our method to other hydrologic fields related to wetness and dryness conditions over the river basins. Following Dai (2011, 2013), which compared observed global aridity changes with model-simulated changes by using Palmer drought severity index (PDSI), we use the Standard Precipitation Index (SPI) to measure drought (McKee et al., 1993). We use SPI as an indicator of drought index because it is based on a simple design and only requires monthly precipitation data. By comparison, PDSI requires precipitation, moisture supply, moisture demand (e.g. evaporation) and loss (e.g. runoff) in hydrologic system (Thornthwaite, 1948). SPI is calculated with the built-in function `dim_spi_n` in NCL (NCAR Command Language) in this study. It is a probability index for which negative SPI values indicate drought, while positive ones indicate wet conditions (see Table 3.3). In the SPI calculation, because precipitation is not normally distributed originally, the precipitation data are transformed and then normalized by using a probability distribution function to represent SPI values as standard deviations from the median. Thus, SPI value can be regarded as the number of standard deviations that the observed value, at certain time, deviates from the long-term mean of the data record.

Another strength of SPI is that it can be computed for different time scales
based on processes affected by atmospheric behavior. The range can be as short as one month or extended to more than 48 months so that it can capture the different scales of short-term or long-term drought.

In the work, we use 3-month SPI. The 3-month SPI analysis provides a comparison of the precipitation over a certain 3-month period in a given year with the same 3-month period for all years (1951 – 2000 in our case) in the precipitation record. We note that a 3-month SPI at the end of August compares the June-July-August precipitation total in that particular year with the June-July-August precipitation totals of all the years. This time scale can reflect short- to medium-term moisture conditions over river basins and provides a seasonal estimation of dryness or wetness based on precipitation. For application to detect available moisture condition for agricultural regions, 3-month SPI might be more applicable compared to other Palmer Indices. The JJA SPI can characterize precipitation tendency for reproductive and early grain-filling period for corn and soybeans for the U.S. Corn Belt. In addition, the MAM SPI can serve as an indicator of soil moisture conditions for the initiation of growing season (more applications can be found at The National Drought Mitigation Center’s website).
Table 3.3: Interpretation of wet (or dry) conditions corresponding to different SPI values. The SPI can be interpreted as the number of standard deviations that the observations deviate from the long-term mean.

<table>
<thead>
<tr>
<th>SPI</th>
<th>Interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td>-3</td>
<td>extremely dry</td>
</tr>
<tr>
<td>-2.5</td>
<td>extremely dry</td>
</tr>
<tr>
<td>-2</td>
<td>extremely dry (SPI &lt; -2.0)</td>
</tr>
<tr>
<td>-1.5</td>
<td>severely dry (-2.0 &lt; SPI &lt; -1.5)</td>
</tr>
<tr>
<td>-1</td>
<td>moderately dry (-1.5 &lt; SPI &lt; -1.0)</td>
</tr>
<tr>
<td>-0.5</td>
<td>near normal</td>
</tr>
<tr>
<td>0</td>
<td>near normal</td>
</tr>
<tr>
<td>0.5</td>
<td>near normal</td>
</tr>
<tr>
<td>1</td>
<td>moderately wet (1.0 &lt; SPI &lt; 1.5)</td>
</tr>
<tr>
<td>1.5</td>
<td>very wet (1.5 &lt; SPI &lt; 2.0)</td>
</tr>
<tr>
<td>2</td>
<td>extremely wet (2.0 &lt; SPI)</td>
</tr>
<tr>
<td>2.5</td>
<td>extremely wet</td>
</tr>
<tr>
<td>3</td>
<td>extremely wet</td>
</tr>
</tbody>
</table>

Figure 3.4 shows the SPI results for selected river basins in specific seasons that showed significant rank correlations. In our case, we have the reconstructed and observational precipitation data (VASClimO) from 1951 – 2000. We use Spearman’s rank correlation coefficient in order to examine whether two variables co-vary and we have n is 50 (DF = 48) and critical value is 0.24 at the significance level of 5%. We observe that our linear model results capture the variability and wetness and drought tendency over 7 of 12 river basins but for only a few seasons. As suggested by Burke and Brown (2008) and Dai (2011), there are still large differences existing in the observed and model simulated drying patterns. Hoerling et al. (2009) also suggest that the recent coupled models do not reproduce observed regional precipitation changes well because natural SSTs variations are poor by understood.
Figure 3.4: Time series plots of SPI (Standardized Precipitation Index) of reconstructed values (thin line) and observational precipitation from VASClimO (colored, thick line) from 1951 – 2000 over selected river basins and seasons that passed (or nearly passed for Nile JJA) the significance test (all river basins at 4 different seasons are tested). \( \rho \) is Spearman’s rank order correlation coefficient. For \( n = 50 \) (df = 48), critical value = 0.24 at the significance level of 5% in our case.
CONCLUSIONS

We have presented the results of applying the linear model to characterize regional climate sensitivity information over 12 river basins to tropical SST anomalies. We can visualize the sensitivity signals and identify what regions in the tropical oceans can strongly influence the regional climate for each basin. Because we focus on the sensitivity signals for each season, we can observe the seasonal changes in both magnitude and locations of the signals. Moreover, sensitivity maps not only indicate the sensitivity of regional response to certain parts of the anomalous SST patterns over tropical ocean, they also provide another way to study how anomalous SST patterns over tropical oceans might result in teleconnection mechanisms.

In simpler terms, the changes of regional climate over certain river basins might be subjected to multiple teleconnection mechanisms. For example, the sensitivity maps of the Indus River basin for precipitation illustrate the fact that the precipitation deficit exits over Indus River basin when El Niño event occurs with abnormal warming in eastern Pacific Ocean (negative sensitivity). However, the
sensitivity maps also denote the important role of how variations in SSTs over the Indian Ocean affect precipitation over the Indus River basin because those SSTs over the Indian Ocean can change the strength of atmospheric subsidence and resulting aridity over India during El Niño events (Ashok et al., 2001; Ihara et al., 2008). As evidence for the combination of these factors, India suffered one of the more severe of recorded droughts in 2002 while having relatively weak El Niño conditions (Rajeevan and McPhaden, 2004; Ihara et al., 2008). This implies that there are not only the anomalous SST patterns over Pacific Ocean but also those in other ocean basins that contribute to the reduction of precipitation over India. Hence, our sensitivity maps give us a good picture of including different anomalous SSTs contribution to the interested river basins and they also provide a starting point to understand how those circulations behave and are captured by the models based on the example above as well as discussions in Chapter 3.

After computing regional climate sensitivity values and creating sensitivity maps for T850 and precipitation, we evaluate the performance of the linear model by reconstructing the regional climate anomalies of T850 and precipitation for 12 river basins. The reconstructed anomalies over river basins are estimated from both sensitivity signal as well as historical SST anomalies. We then compare the reconstructed results to ensemble-averaged AMIP results and estimate the correlation between the two time series. We find a statistically significant response of the linear method over most of river basins in general (Table 3.1 in Chapter 3).
We also compare the linear model with observed data and as expected, the correlations are not as high as those with AMIP because observational data include more uncertainties and variability that the linear method could not capture. There might be other reasons that the linear model will not reproduce observations. Primarily, the method focuses on the contribution of anomalous SSTs and thus it cannot characterize other individual processes in the atmosphere that contribute to climate feedback such as aerosols, clouds or sea ice might bring to changing precipitation. Also, the linear method might fail to detect the effects and their magnitude that multiple teleconnections can influence regional climate as the example illustrated for Indus River basin. However, despite these issues, the results we have demonstrate the potential predictability of the linear model for predicting temperature and precipitation over the specific river basins at seasonal and longer timescales. In addition, the ability to assess both the successful and unsuccessful results by using linear model over different river basins at different timescales is equally important in the study.

As discussed in previous chapters, SST anomalies over tropical oceans have demonstrated their impact on regional climate as well as for other fields like hydrology, agriculture and economics around the world via ocean-atmosphere-land teleconnections. Therefore, we chose to address one application by examining a drought index in this study. The ability to forecast the magnitude and timing of regional precipitation anomalies over river basins allows people to prepare themselves
for better water usage and it can ameliorate the living and agricultural planning. Because we know that hydrologic changes over river basins are associated with the variability of SST anomalies, we anticipate that the application of our linear model can become a useful tool for communicating critical information of regional climate changes in response to SST anomalies as useful seasonal forecasts of SST are available. One goal of this work is to make the linear model available to use in other climate-related fields provided it is sufficiently efficient and robust. We expect the information could be useful for policy makers, decision makers and institutions requiring regional climate change assessments.
Despite the success of the linear model, we discuss some uncertainties that are difficult to quantify or characterize. These features might generally not be described by simple linear trend analysis due to internal variability or other uncertainty. One concern is that the regional response over river basins in certain geographic regions to anomalous SST forcing does not show linear behavior. This can be either because the true forcing is not specified in our linear model, or because the true dynamics in the atmosphere cannot be represented using a linear model. For example, the method does not include the feedback on SST changes forced by teleconnection response to SST anomalies. One example is the teleconnection between East African rainfall and ENSO that has been identified as a link between ENSO and the Indian Ocean Dipole (IOD) (Black, 2005; Shi et al., 2007). A strong El Niño forcing in the boreal autumn can result in sufficient cooling in the western
Indian Ocean and thus trigger an IOD event, which would subsequently cause high rainfall in East Africa. These features are hard to identify using an AGCM forced by SST patterns as compared to a full AOGCM or an AGCM with a slab ocean model. For example, anomalous SST patterns can change the sea level pressure and create pressure gradients between two locations so that it can induce surface wind and result in a mixing over the upper ocean layer. This can then reduce the SST anomaly patterns and further change the circulation. Therefore, these are deficiencies we should consider when using an AGCM that cannot capture all processes.

Though the mathematical part of the linear model is simple by design, the dynamical aspects of uncertainties in regional climate prediction remain difficult to include in the analysis. The climate model cannot either simulate some important hydrologic variables well (i.e. stream flow, run-off etc.) due to their time lag associated with storage in river basins (Milly et al., 2005). Therefore, understanding uncertainties in regional predictions is another important issue and many approaches are necessary to solve specific problems.

As discussed earlier, owing to the chain of events causing teleconnection patterns, it can be expected that nonlinearities in the regional response could be related to physical processes such as the local nonlinearities in variables over river basins. In this study, missing forcings may contribute to regional climate change that our model did not capture, such as greenhouse gases, aerosols, radiation or
other regional effects. In addition, regional climate could be dominated by variability from other factors such as land processes, sea ice changes or similar features (e.g. Pitman and Narisma (2005); Maslowski et al. (2012)). Therefore, inconsistency between the results from the linear model and the observational data can occur when the linear signal is a weak contributor to local variations compared to the response to sources of variability in the system. When considering internal and forced variability, uncertainties in the response to forcing are generally larger for precipitation than for temperature. Therefore, the reconstructed T850 results are generally better than precipitation. In addition, the reconstructed variables for extratropical river basins might experience more internal and forced variability than those in tropical regions. As Li et al. (2012) discuss (shown in Figure 12 in Li et al. (2012)), if one uses correlation as a measure of predictability of the regional climate change, the river basins with smaller internal and forced variability in the tropics generally have higher potential for predictability of temperature. The ratio of forced to internal variability on inter annual times scales (i.e. signal-to-noise ratio) may be used to indicate the predictable skill for regional precipitation. The river basins with a larger ratio demonstrate higher level of predictability with specified SST forcing for precipitation.

Regional climate change detection problems are still considerably more challenging than the global problem because more precise data are required for smaller spatial scales (Zwiers and Zhang, 2003; Hegerl et al., 2007). To make regional cli-
mate change detection results more robust, a better understanding of the sources of variability and potential uncertainties in these estimates are required. However, our preliminary sensitivity maps for precipitation show that the regional responses over river basins depend on the pattern of tropical SST variations throughout the year. Here we initially only focus on the influence of tropical SSTs and the dynamical response of atmosphere by using the results from CAM3.1 and whether those signals can be captured by using the linear model applied in the work.

Considering potential improvements we can make for our method, we can apply downscaling technique to assess hydrological impact of regional climate change over river basins in the future. One of our goals is to extract hydrologic information from GCMs by using our linear model to predict seasonal or longer timescale information that can be incorporated into hydrological models for regional climate assessment. We know that in addition to precipitation, hydrologic processes lie in much smaller scales differences exist for spatial scales between climate models and hydrological models. Therefore, it is necessary to apply suitable downscaling techniques that can provide policy makers with more reliable assessment at appropriate scales. This requires significantly more work because many approaches exist for downscaling results from climate models and incorporating them into hydrologic simulations (e.g. Wood et al. (2004)).

The linking between temperature, precipitation and drought indices over river basins and patterns of SST anomalies is just a first step to characterize changes
in hydroclimatology related to anomalous tropical SST fields. Other variables like river flow, runoff and resulting application associated with crop or wheat yield will be examined in the future; however, those variables are more difficult to deal with because current climate models cannot capture important hydrologic variables well (e.g. streamflow or run-off) due to the time-lag associated with storage in river basins (Milly et al., 2005). Although many uncertainties still exist in regional climate prediction and they are sufficiently difficult to be resolved shortly, we expect that our method can provide useful information, based on its simplicity and efficiency, into the decision-making model.


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