INVESTIGATION INTO REGIONAL CLIMATE VARIABILITY USING TREE-RING RECONSTRUCTION, CLIMATE DIAGNOSTICS AND PREDICTION

by

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ABSTRACT

Investigation into Regional Climate Variability using Tree-Ring Reconstruction, Climate Diagnostics and Prediction

by

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Utah State University, 2016

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This document is a summary of research conducted to develop and apply climate analysis tools toward a better understanding of the past and future of hydroclimate variability in the state of Utah. Two pilot studies developed data management and climate analysis tools subsequently applied to our region of interest. The first investigated the role of natural atmospheric forcing in the inter-annual variability of precipitation of the Sahel region in Africa, and found a previously undocumented link with the East Atlantic mode, which explains 29% of variance in regional precipitation. An analysis of output from an operational seasonal climate forecast model revealed a failure in the model to reproduce this linkage, thus highlighting a shortcoming in model performance. The second pilot study studied long-term trends in the strength of the Great Plains low-level jet, a driver of storm development in the region’s wet spring season. Our analysis showed that since 1979 the low-level jet has strengthened as shifted the timing of peak
activity, resulting in shifts both in time and location for peak precipitation, possibly the result of anthropogenic forcing. Our third study used a unique tree-ring dataset to create a reconstruction of April 1 snow water equivalent, an important measure of water supply in the Intermountain West, for the state of Utah to 1850. Analysis of the reconstruction shows the majority of snowpack variability occurs monotonically over the whole state at decadal to multidecadal frequencies. The final study evaluated decadal prediction performance of climate models participating in the Coupled Model Intercomparison Project 5. We found that the analyzed models exhibit modest skill in prediction of the Pacific Decadal Oscillation and better skill in prediction of global temperature trends post 1960.
PUBLIC ABSTRACT

Investigation into Regional Climate Variability using Tree-Ring Reconstruction, Climate Diagnostics and Prediction

Daniel A Barandiaran

This document summarizes research conducted to develop and apply climate analysis tools toward a better understanding of the past and future of climate variability in the state of Utah. Two pilot studies developed analysis tools through the investigation of natural variability in precipitation systems in Africa, and research into long-term changes and trends in spring rainfall over the U.S. Great Plains. Our third study used tree-ring data to estimate snowpack in the state of Utah to 1850, doubling the length of record and offering a better understanding of the history of snowpack in the state. Our final study looked at a suite of climate models to test their ability to make multiyear predictions of factors that affect climate in the Utah region.
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CHAPTER 1
INTRODUCTION

Climate research has undergone profound changes in the last few decades. This is the result of both an increase in the availability and quality of observational data and advances in computer-driven climate models. Analysis of observational data form a foundation for our understanding of dynamic processes in the climate system and give us a basis for constraints on extreme events. Climate system models provide a framework to test theories on climate processes and also provide a way to simulate future climate on a variety of time scales.

The quantity of climate data now available is staggering large, on the order of thousands of terabytes. Given such a huge pool of information to draw from, sophisticated tools and techniques must be applied to acquire, manage, process and analyze the available data. Powerful statistical methods such as canonical correlation analysis, empirical orthogonal functions, spectral analysis and regression models have become commonplace in climate analysis, enabling researchers to determine patterns and relationships in ever-larger datasets. Thus, a successful climate scientist must be able to 1) understand the use of such tools and 2) be able to apply them to very large datasets.

These tools have led to large strides in the understanding of Earth’s climate system. A well-known example of this progress is the state of understanding and continuing research on the global climate phenomenon known as El Niño-Southern Oscillation (ENSO). First discovered in the early 20th Century, it is now a phenomenon that is familiar outside the scientific community and even has made its way into popular
culture, and there is an extensive literature on the driving mechanisms, global effects and potential of forecasting for this climate feature.

ENSO is probably the best-known climate phenomenon, and due to its wide-reaching effects on global weather patterns it receives the most attention both inside and outside the scientific community. There are however many regions for which there is a minimal effect on local climate as a result of ENSO, and there are many other forcing factors on global weather patterns, and so research must necessarily look beyond El Niño to gain a better understanding of the global climate.

Such research is of great value to society. There are many hazards associated with weather and climate, so a better understanding of weather and climate systems lead to a greater potential to anticipate and prepare for these threats. In the face of growing populations and with the emerging problem of climate change, human societies face many challenges; one such challenge is the effective management of freshwater supplies, a crucial resource for all human endeavors. Since water availability is so closely tied to weather and climate, a key component for planning and management of water resources must be a strong understanding of global and regional hydroclimate. Indeed, this is a major component of climate research, and will be the focus of this dissertation.

**OBJECTIVES**

The main goal of this research is to apply current climate diagnostics techniques to various climate regimes, specifically with the aim to develop tools that would be useful toward management of freshwater resources. The following objectives are addressed to accomplish the main goal:
1) To develop hydroclimate analysis and climate model evaluation tools for use in subsequent objectives, and test their application in various climate regimes.

2) To extend our knowledge of recent Utah hydroclimate by using tree-ring data to reconstruct a history of mountain snowpack, an important source of Utah’s freshwater.

3) To evaluate current climate models’ ability to predict major drivers of both global and Utah hydroclimate, and pending their performance, to offer a forecast for regional freshwater resource supply.

The first objective was accomplished with two pilot studies. The first examined inter-annual variability of precipitation in the Sahel region of Africa, which found a previously undocumented link with conditions in the North Atlantic. We also conducted an evaluation of the National Oceanic and Atmospheric Administration (NOAA) Climate Forecast System (CFS), which showed that the model lacked the ability to reproduce variability as revealed by our analysis. These findings are highlighted in Chapter 2. The second study examined the Great Plains low-level jet, a circulation feature that forms during the spring over the central U.S. and is an important driver of precipitation systems in the region. We found a long-term trend of strengthening of the low-level jet, which has led to a temporal and spatial shift in precipitation patterns over the Great Plains. Details of this study are found in Chapter 3.

The second objective was accomplished using tree-ring data collected by the U.S. Forest Service and processed by the USU Dendrochronology Laboratory to create a
gridded reconstruction of Utah snowpack at a 4km resolution back to 1850. Analysis of the reconstruction revealed quasi- and multi-decadal variability consistent with studies of observed and reconstructed hydroclimate. Results of this study are detailed in Chapter 4.

The third objective was accomplished through analysis of data created for the Coupled Model Intercomparison Project, version 5 (CMIP5), a multinational effort to create a series of controlled experiments through which current climate models’ performance could be evaluated. We specifically evaluated the decadal prediction experiments, determining model skill in reproduction of the Pacific Decadal Oscillation and Atlantic Multidecadal Oscillation, two modes of variability in the oceans that act as important drivers of Earth’s climate. Models were found to have little skill in prediction of these ocean indices, but showed strong performance in reproduction of global average surface temperature post-1960. These findings are described in Chapter 5. Some final discussion and conclusions wrap up this dissertation in Chapter 6.
CHAPTER 2

THE MISSING TELECONNECTION BETWEEN THE NORTH ATLANTIC AND SAHEL PRECIPITATION IN CFSV2

Abstract

This study presents findings on the link between inter-annual variabilities of atmospheric circulations over the North Atlantic and precipitation over the African Sahel ($P_S$). Our analysis shows that a meridionally stratified circulation wave train, with resemblance to the East Atlantic (EA) mode, is apparently connected to $P_S$. This EA-$P_S$ connection likely takes place through Rossby wave dispersion in the middle troposphere originating from the mid-latitude North Atlantic. However, the Climate Forecast System version 2 fails to depict this EA mode and its $P_S$ impact. Because the EA mode explains about 29% of variance of $P_S$, the result is suggestive of a comparable portion of $P_S$ variability that is missing in the seasonal forecast.

1. Introduction

The African Sahel, a semi-arid region lying along the southern edge of the Sahara Desert, is characterized by large climate variability in summer precipitation on inter-annual and inter-decadal time scales. The El Niño-Southern Oscillation (ENSO) is known as an important modulator of Sahel summer precipitation ($P_S$) (e.g., Semazzi et al. 1988; Janicot et al. 1996; Joly and Voldoire, 2009). Other climatic forcing factors that

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modulate $P_S$ include sea surface temperature (SST) anomalies in the Indian Ocean (Bader and Latif, 2003) and the tropical Atlantic (Brandt et al., 2010), as well as the Atlantic Multi-decadal Oscillation (AMO) (Zhang and Delworth, 2006). These previous findings were based upon the concept of SST-driven, tropically confined teleconnections affecting $P_S$. Changes in SSTs also can modulate planetary-scale circulation, such as modifying the strength of the Hadley cells and changing the position of the extratropical storm tracks (Brayshaw et al., 2008, Graff and LaCasce, 2012).

There are, however, some studies that hint at teleconnectional forcing of $P_S$ from the mid-latitudes. Focusing on the North Atlantic Oscillation (NAO; Hurrell et al., 2003) during summer months, Folland et al. (2009) found that temperature and precipitation in the Sahel are correlated with NAO. Chen and Wang (2007) noticed a connection between $P_S$ and an atmospheric short-wave train in the North Atlantic during active ENSO years. In this study, we show a meridional wave train pattern that connects $P_S$ with a possible higher latitude influence, regardless of the state of ENSO. Our analysis indicates that such a North Atlantic wave train is linked to the so-called East Atlantic (EA) mode. The EA was first identified by Barnston and Livezey (1987) as a center of anomalous 700mb geopotential height off the coast of Ireland accompanied by wave-like disturbances across Europe. We also report that this EA-$P_S$ linkage is missing in one of the major climate forecast models, hence representing missing variability of $P_S$ in seasonal climate prediction.

This study utilized the National Center for Environmental Prediction (NCEP)/National Corporation for Atmospheric Research (NCAR) Reanalysis I (Kalnay et al., 1996) for atmospheric data. Rain gauge observations compiled and gridded by the
National Oceanic and Atmospheric Administration (NOAA) precipitation reconstruction over land (PREC/L; Chen et al., 2002) were used. The reforecast outputs (or hindcast) from the NCEP Climate Forecast System version 2 (CFSv2; Saha et al., 2012) were examined for the forecast skill of $P_S$ and EA. $P_S$ was defined as the average precipitation within 12°-20° N and 15° W-30° E; hereafter the term $P_S$ and all other analyses are focused on the July-September (JAS) season. Precipitation and various climate indices used in the following analyses were normalized by standard deviation for ease of comparison, and all data were linearly detrended to remove any anthropogenic forcing while retaining decadal-scale variability such as the recovery of the Sahel drought (e.g., Fink et al. 2010; Wang and Gillies 2011).

2. The North Atlantic influence on $P_S$

2.1. Empirical evidence

The well-known ENSO influence on $P_S$ is illustrated in Figure 1a by the composites of streamfunction anomalies during ENSO-active years, i.e., La Niña minus El Niño years based on normalized JAS Niño3.4 index $> 1.25$, for the period 1950-2010 (Niño3.4 index obtained from the NOAA Climate Prediction Center (CPC; http://www.cpc.ncep.noaa.gov/products/precip/CWlink/MJO/enso.shtml). These composites reflect the resultant wet conditions in the Sahel during ENSO-active years. There is a broad area of increased anticyclonic flow at 200 mb over the Mediterranean Sea, North Africa and the tropical Atlantic, with weaker cyclonic anomalies in the middle and lower troposphere over North Africa. During La Niña (El Niño) events, the
circulation anomalies result in increased (decreased) strength of the tropical easterly jet (TEJ) and enhanced (suppressed) divergence aloft, which in turn enhances (suppresses) convection over the Sahel and West Africa (e.g. Fontaine *et al.*, 1995). The anomaly at 600mb over North Africa is important in that it represents a modulation of the African easterly Jet (AEJ), whose strength and position plays an important role in the development of African easterly waves (AEW, Thorncroft and Hoskins, 1994; Chen, 2006; Nicolson and Grist, 2011).

Composite circulation anomalies for wet minus dry years (i.e. when $|\text{normalized } P_3| > 1.25$) in Figure 1b, compiled during ENSO-neutral years (i.e. $|\text{normalized JAS Niño3.4 index}| < 0.75$), show some similarities with the ENSO composite, but with some important differences. Both cases reveal cyclonic anomalies in the middle and lower troposphere, but the ENSO-neutral composite has a stronger cyclonic anomaly over Great Britain at all levels, especially at 200 mb. Second, there is a northwest-southeast oriented wave train extending from Greenland to Eurasia particularly at 200mb, which includes the pronounced negative anomaly over the British Isles. At 850mb the cyclonic anomaly over the Sahel implies increased monsoonal southwesterly flows, thereby enhancing low-level moisture flux from the Gulf of Guinea; this feature is present in both composites, but is stronger and more coherent in the ENSO-neutral ‘wet’ case.

The meridional wave train pattern revealed in Figure 1b resembles the spatial loading pattern of the EA (Barnston and Livezey, 1987). Based upon the EA index obtained from NOAA CPC (http://www.cpc.ncep.noaa.gov/data/teledoc/ea.shtml), the streamfunction anomaly composites during EA-active ($(EA \text{ index } > 1.25) - (EA \text{ index } <$
ENSO-neutral years are shown in Figure 2a, which depict the characteristic anomalous center west of Ireland and the wave train extending over Europe. Because the NCEP/NCAR reanalysis was produced from assimilation systems that are two decades old, we also compared against the newer, but shorter-duration NCEP/Department of Energy (DOE) Reanalysis II (Kanamitsu et al., 2002) and the CFS Reanalysis (Saha et al., 2010) during their respective time periods and found the results from both reanalyses to be equivalent (not shown).

By correlating $P_s$ with the EA index, we found that there is indeed a statistically significant relationship (Figure 2b, $r=0.54$, $p < 0.01$). Based upon their correlations with $P_s$ during the period 1950-2010 (i.e. $r^2$), ENSO explains 11% of the variance of $P_s$ while EA explains 29%. Spatial correlations between EA and PREC/L precipitation (Figure 2c) depict a significant, positive relationship across the Sahel region (boxed area). This correlation map also reveals a north-south stratification that corresponds to the EA circulation pattern (Figure 2a).

2.2. Dynamical inference

Having demonstrated the empirical connection between EA and $P_s$, we next explored the dynamic mechanism of this connection by analyzing the horizontal-component Rossby wave-activity flux ($W$) for our composites. We derived the formulation of $W$ by following Takaya and Nakamura (2001),

$$W = \frac{1}{2|U|} \left[ u(\psi_x^2 - \psi_y \psi_{x\gamma}) + v(\psi_x \psi_y - \psi \psi_{xy}) \right]$$
where $U$ is the two-dimensional JAS mean flow ($u,v$) and $\psi$ is the perturbation streamfunction, with subscripting representing partial derivatives. This $W$ vector provides a measure of propagating Rossby wave energy. Calculation of this wave-activity flux is not dependent on spatial or temporal averaging and therefore is applicable for any particular time period (see Takaya and Nakamura, 2001 for details).

To capture and isolate the wave train that is characteristic of the EA, we conducted an Empirical Orthogonal Function (EOF) analysis of 600mb geopotential height over the North Atlantic, Europe and North Africa only (20N-90N, 100W-60E), so as to disregard potentially confounding climate signals from the rest of the Northern Hemisphere. The 600mb level was chosen to focus on the height at which the core of the AEJ is located. The resulting analysis yields an EA-like pattern for in the second mode (the first being NAO). The corresponding time series is a reasonable representation of the globally and 700mb-based EA index ($r=0.58$), and broadly captures the interannual and interdecadal variability of the EA (not shown). Using this EOF-based EA index when |normalized EOF time series| > 1.25 and during ENSO natural years, the EA circulation patterns are again reconstructed in Figure 3a with the geopotential height – i.e., with a regional weighting over the North Atlantic and Africa. When compared to the ENSO composite in Figure 3b, the meridional wave train pattern in this EA composite is much more pronounced in the middle and lower troposphere.

During ENSO-active years (Figure 3b), Rossby wave-activity flux is confined to the upper troposphere and directs from North Africa towards Europe, implying the movement of energy from the tropics to the middle latitudes. By contrast, in EA-active years (Figure 3a – during ENSO-neutral years) the wave-activity flux at the upper
troposphere (200 mb) is mainly oriented towards southeast but is confined to north of 30° N. However, in the middle troposphere (600 mb) the wave-activity flux penetrates into North Africa along the downstream portion of the wave train over the Mediterranean Sea. At lower troposphere (850 mb), the wave-activity flux becomes weaker and is mostly confined to the anomaly off the coast of Ireland. This $W$ propagation is a manifestation of the forcing mechanism leading to the middle tropospheric circulation patterns associated with the Sahelian wet/dry anomalies (Figure 1b).

The wave-activity flux over North Africa at 600mb has an implication for regional circulation anomalies. It appears that the mid-level anticyclone that stations itself over the Sahara Desert can be modulated by teleconnection emanating from higher latitudes, i.e. it oscillates in response to the wave train initiated during positive/negative EA years. This teleconnection may affect the position and/or intensity of the AEJ, which in turn regulates the activity of African easterly waves (AEWs) (Thornicroft and Hoskins, 1994; Chen, 2006). For instance, Wang and Gillies (2011) found that the post-1990 recovery of the Sahel drought, i.e., the so-called Sahel greening (Herrmann et al., 2005; Olsson et al., 2005), occurred in association with the northward migration of both the AEJ core and the AEW activity, leading the summer rain band to move northward. Because AEWs form at both sides of the AEJ core (Reed, 1988; Chen, 2006), it is possible that this injection of Rossby wave energy weakens (strengthens) the middle-level anticyclone during high EA-index (low EA-index) years. This would then affect the AEJ, as well as the activity of AEWs, thereby influencing $P_s$. Further investigation is needed to detail the dynamic processes of this EA-$P_s$ teleconnection.
3. Forecast skill for EA

An important question derived from the aforementioned finding of the EA-P$_S$ connection lies in its depiction in climate prediction, that is, how well do operational climate forecast models capture EA and its impact on P$_S$? To examine this, we analyzed hindcast output from the CFSv2 to evaluate the model’s performance. Following the methodology used by the CPC to calculate EA, we first conducted a rotated EOF analysis on the Northern Hemispheric, 500mb geopotential height of the CFSv2 at zero-month lead time. The first 10 principal components are plotted in Figure 4. The loading patterns for some of the EOFs are similar to the EA pattern, but those EOFs did not have a corresponding time series that correlated significantly with either the EA index or P$_S$ (not shown). Apparently, CFSv2 was unable to reproduce EA through the EOF approach as was used in Barnston and Livezey (1987) and the CPC.

Seeking a more direct comparison, we conducted spatial correlations instead. We first computed the correlations between the reanalysis 500mb geopotential height and the EA and ENSO indices, and then preformed the same correlations using the CFSv2 zero-month reforecast (Figure 5). As can be seen, the atmospheric response to teleconnectional forcing is substantially different between the reanalysis and CFSv2 reforecast. When considering ENSO forcing, reanalysis shows positive correlation between geopotential height in North Africa (Figure 5a), while the CFSv2 reforecast (Figure 5c) shows a much more local positive response over the Sahara Desert and a negative relationship over Central and South America – in disagreement with reanalysis. Similarly, spatial correlation of the EA index with reanalysis (Figure 5b) depicts the
distinct wave train over Europe and the negative anomaly west of Ireland, while CFSv2 does not reproduce the wave train (Figure 5d) and, furthermore, reveals an opposite relationship over the North Atlantic.

In terms of the Niño-3.4 index, CFSv2 does reproduce well \((r=0.97)\) and also reasonably captures \(P_S\) \((r=0.78)\) at 0-month forecast. At forecast month 3, CFSv2 still has a robust correlation of 0.81 for Niño-3.4, but the correlation of \(P_S\) drops to 0.33 (insignificant). As has been shown earlier, the model has difficulties in reproducing the atmospheric response to ENSO. Regarding EA and its association with \(P_S\), the CFSv2 appears to fail in all forecast months, hence missing nearly 30% of the \(P_S\) variance that is explained by EA.

4. Summary

Analysis of the Sahel rainfall anomalies \((P_S)\) during ENSO-neutral years shows that, in addition to its known connection with ENSO, \(P_S\) is significantly and positively correlated with EA. During the positive phase of EA, fluxes of Rossby wave activity bring energy dispersed from the mid-latitudes into North Africa; this process is particularly pronounced at the middle troposphere where the core of the AEJ is located. However, the CFSv2 fails to capture the EA mode and its association with \(P_S\). On the other hand, the CFSv2 produces reasonable ENSO states as well as the associated \(P_S\) variation up to 3 months.

CFSv2 has been improved in terms of forecasting ENSO, particularly SST evolutions in the Niño-3.4 region (e.g., Wu et al., 2009; Zhu et al., 2012). This is a promising step in forecasting the well-established connection between ENSO and \(P_S\).
Correspondingly, modeled $P_S$ responds appropriately to ENSO forcing through the first few forecast months. However, there is a discrepancy in the variability of atmospheric circulations in the North Atlantic and North Africa between the CFSv2 and reanalysis data, in that EA is not captured at all even at 0-month forecast. Therefore, seasonal prediction of $P_S$ will likely suffer from the inability of CFSv2 in depicting EA. The only remedy at this point in time is to either develop empirical method supplementing the EA-related prediction or engaging multi-model ensembles, similar to what has been developed for the difficult-to-forecast NAO (Orsolini, *et al*., 2011, Jia, *et al*., 2012).

Finally, because EA is predominately a winter mode (whereas this study only considers the summer season), further examination of model performance in the wintertime atmospheric variability could help determine if this deficiency of EA forecasting is seasonal in nature, or is intrinsic to CFSv2 regardless of season. In future work we also will further explore the transfer of mid-latitude energy to the African subtropical climate that is implied by the Rossby wave-activity flux.

**References**


Figures 2-1. Composite differences of streamfunction over the years 1950-2010 during (a) La Niña summers (normalized Niño 3.4 index <-1.25) minus El Niño summers (Niño 3.4 index >1.25), and (b) wet summers (normalized P_s >1.25) minus dry summers (normalized P_s <-1.25) during ENSO-neutral years (normalized Niño 3.4 index between -0.75 and 0.75). Stippling indicates statistical significance of 95% per t-test.
Figure 2-2. (a) Streamfunction anomalies during positive EA index years (normalized EA index > 1.25) minus negative EA index years (normalized EA index < -1.25), during EHSO-neutral years (normalized NINO3.4 index between -0.75 and 0.75). (b) Time series for normalized EA index (black) and P5 (green). (c) Spatial correlation map between EA index and PREC/L precipitation. Red box indicates Sahel region.
Figure 2-3. Geopotential height anomalies (contours) and Rossby wave-activity flux vectors for (a) High regional EOF time series values (normalized PC > 1.25) minus low regional EOF time series (normalized PC < -1.25) during ENSO-neutral years (normalized Nino3.4 index between -0.75 and 0.75) and (b) La Nina summers (normalized Nino3.4 index < -1.25) minus El Nino summers (Nino3.4 index > 1.25).
**Figure 2-4.** First 10 leading modes of rotated EOF analysis on CFSv2 500mb geopotential height.
Figure 2-5. Spatial correlation patterns between NCEP1 500mb geopotential height and (a) Nino3.4 index, (b) EA index. CFSv2 reforecast 500mb geopotential height and (c) Nino3.4 index, (d) EA index.
CHAPTER 3

OBSERVED TRENDS IN THE GREAT PLAINS LOW-LEVEL JET AND ASSOCIATED PRECIPITATION CHANGES IN RELATION TO RECENT DROUGHTS

Abstract

Recent drought over the Great Plains has had significant impacts on agriculture and the economy, highlighting the need for better understanding of any ongoing changes in the regional hydroclimate. Trends in the Great Plains low-level jet (GPLLJ) during the months April-June (AMJ) and associated precipitation are analyzed using the North American Regional Reanalysis (NARR) for the period 1979-2012. Linear trends computed for meridional winds and precipitation intensity, frequency and total across the Great Plains show that (1) the GPLLJ has strengthened and expanded northward and (2) precipitation has decreased substantially in the Southern Plains while increasing in the Northern Plains. Particularly in May, the rainy season in the Oklahoma-Texas region, precipitation has migrated northward in correspondence to the shifted northern edge of the GPLLJ, leading to near 50% declines in precipitation since 1979. These observed changes are discussed in the context of recent droughts and projected climate for the region.

1. Introduction

In the Midwest and Great Plains of the United States agricultural production relies heavily on spring and summer precipitation, and variability of this water resource has profound impacts on farms and ecosystems alike. Extreme weather and climate events such as the floods of 1993 and 2008 or the droughts of 1988 and 2011-12 led to profound hardship and economic disruption for the region [Basara et al., 2013]. In addition to known extreme events, anecdotal evidence suggests that the seasonal precipitation in the Northern Plains (Nebraska, South/North Dakota), which historically has peaked in summer, is shifting to a regime similar to that of southern states (Oklahoma and Texas), which usually receive the most rain in late spring [Bob Oglesby, 2013, personal communication]. Thus, it is crucial to understand the driving forces behind such weather/climate extremes under changing climate patterns of the Great Plains.

One of the atmospheric circulation systems closely connected to the region’s seasonal precipitation is the Great Plains Low-Level Jet (GPLLJ), which is primarily a transient pattern of nocturnal strong winds just above the surface [i.e., below ~1000 m. AGL; Stensrud, 1996]. The GPLLJ transports water vapor from the Gulf of Mexico (GOM) and provides low-level moisture convergence at its northern edges, facilitating the formation of convective precipitation [Higgins et al., 1997]. There have been numerous studies that outline the synoptic climatology [Mitchell et al., 1995; Wang and Chen, 2009], inter-annual variability [Weaver and Nigam, 2007], and possible future changes of the GPLLJ [Cook et al., 2008].
Here we present findings on observed changes in the GPLLJ and concurrent changes in seasonal precipitation characteristics. We use the North American Regional Reanalysis [NARR; Mesinger et al., 2006] both for wind and precipitation data. NARR uses an assimilation scheme that incorporates rain gauge data, and has been shown to adequately reproduce precipitation over the contiguous U.S. [Bukovsky and Karoly, 2007]. NARR was specifically chosen because of its high spatial (~32km) and temporal (3-hr) resolutions, which therefore resolves the GPLLJ and associated precipitation in greater detail. Since our analysis focuses on trends we compared NARR with the daily precipitation reanalysis of Higgins et al. [2000] and found no significant trend in the difference between datasets, so we assume that any model bias present in NARR precipitation is consistent and does not introduce any spurious trend in our analysis.

2. The Spring Rainy Season

Over the Central U.S., warm-season precipitation migrates from the southern Great Plains in spring to the upper Midwest in summer. Both rainfall and convective storm activity reach their maximum in May and June in the Great Plains forming a precipitation center over eastern Oklahoma and northeastern Texas [Wang and Chen, 2009]. This rainfall maximum is depicted in Figure 1a by the second leading empirical orthogonal function (EOF) of monthly long-term mean precipitation. The corresponding principal component (PC) time series in Figure 1b reveals elevated seasonal precipitation from April through June (AMJ), peaking in May. However, over the past three decades the amount of spring precipitation in the region has declined. Figure 1c shows time series of pentad (5-day) mean precipitation averaged within the Oklahoma-Texas region
(outlined in Figure 1a) for the period 1979-1995 (red) versus 1996-2012 (blue), with the percent difference between the two periods (yellow line). There is a clear reduction in AMJ rainfall, particularly the entire month of May during which deficits of as much as 50% are observed. Such a reduction in rainfall signifies the decline of a vital water source during the rainy season in this Oklahoma-Texas region.

The association between the GPLLJ and daily rainfall systems is illustrated in Figure 2, i.e. Hovmöller diagrams of the 3-hourly precipitation and meridional wind (v-component of wind) speed at 925 mb (the core level of the GPLLJ), averaged over the latitude range from the box in Figure 1a, and help to depict the daily evolution of weather. We present four cases: two are wet years (1987 and 1992) and two are dry years (2010 and 2012). During the wet years the strength of the GPLLJ is much less than during dry years, and the largest concentration of rainfall occurs in late May. In contrast, during dry years the month of May is noticeably drier, and the GPLLJ is much stronger and more frequent throughout AMJ. Also in these cases, dry spells are almost always accompanied by episodes of a strong GPLLJ.

There is an apparent inverse relationship between the general strength of the GPLLJ and the amount of rain in this region during spring. Such a relationship has been documented in previous works [Higgins et al., 1997; Weaver and Nigam, 2008], and reflects the fact that in order to provide the appropriate moisture convergence the GPLLJ must have its northern edge right over the Oklahoma-Texas area, without overshooting the region.
3. Long-Term Changes in the Spring Rainy Season

Cook et al. [2008] have found that increased greenhouse gases would modify and eventually increase the strength of the G PLLJ. Weaver and Nigam [2008] found a noticeable intensification of the springtime GPL LJ up to year 2001, and noted the relationship between the strength of the GPL LJ and the distribution of precipitation in the Midwest. However, neither study established a link of the springtime GPL LJ tendency with increased dryness in the Oklahoma-Texas region. Thus, we next examine the extent to which the GPL LJ has changed, and how this corresponds to the precipitation decrease and recent droughts in the region.

Focusing on AMJ, Figure 3 shows a series of latitude-time Hovmöller diagrams to depict the 1979-2012 change of the GPL LJ for each month. First, the left-most column (Figure 3a) depicts the climatological precipitation overlaid with 925-mb wind vectors for geographical reference. The white box in Figure 3a indicates the sub-region over which averages were calculated in subsequent panels. In Figures 3b-e, each panel presents a different variable averaged over the sub-region. To construct these plots the trend for all latitudes is calculated using linear least-squares regression for 6-hourly 925-mb v-wind strength (Figure 3b), average precipitation intensity (Figure 3c), monthly frequency of rain (Figure 3d) and monthly total precipitation (Figure 3e). Rainfall frequency is defined as the number of 6-hourly time steps per month in which accumulated precipitation exceeds 1 mm. Latitudes in which the regression coefficient is significant at 95% confidence are indicated along the y-axis. Note that these diagrams
are linear trends added on the long-term mean, similar to a smoothed version of the monthly mean values plotted over time.

For all three months of AMJ there is an apparent increase in the strength of $\nu$-wind for the southern portion of the domain, particularly between $30^\circ$N-$35^\circ$N including the GOM (i.e. upstream of the GPLLJ). There is also a northward migration of the maximum gradient of $\nu$-wind speed, and the resultant convergence at the exit region of the GPLLJ. Correspondingly, the changes in total precipitation (Figure 3e) reveal a northward migration especially in May; in April there is a positive trend in precipitation from $32^\circ$N-$45^\circ$N with the greatest increases at $\sim35^\circ$N, suggesting a shift in the position of the spring center shown in Figure 1a. Accompanying this northward migration of precipitation is a concurrent increase and migration in rainfall frequencies and overall precipitation intensity (Figures 3c, d), particularly in May.

Perhaps the most profound implication of these migrating precipitation characteristics is the drying trend in the Oklahoma-Texas region. In May, the precipitation reduction is directly linked to the decreasing frequency of rain events and reduced rainfall intensity, along with the strengthened GPLLJ. In June the greatest change in precipitation is found south of $34^\circ$N showing a negative trend in the frequency of precipitation. North of this latitude trends for total precipitation approach zero, but there is a narrow band from $36^\circ$N-$40^\circ$N in which precipitation intensity has increased, yet precipitation frequency has decreased. This increase in precipitation intensity is collocated with a slight increase in total precipitation, suggesting less frequent but stronger storms. These changes in precipitation characteristics are apparently linked with the change in the GPLLJ. As the jet intensifies and expands northward, its migrating
northern boundary (or v-wind gradient) enhances precipitation activity to the north due to increased convergence, but weakens it in the south due to increased divergence.

These results point to the changing GPLLLJ dynamics in the spring rainy season, and raise questions about possible changes in moisture supply. We therefore look at trends in water vapor over the GOM, i.e., the GPLLLJ moisture source region, measured by the Special Sensor Microwave Imager (SSM/I+SSMIS), which provide robust retrievals of water vapor for climate monitoring [Wentz and Schabel, 2000; Mears et al., 2007]. The polar-orbiting SSM/I sensors provide as many as two observations per day at a particular location. We used the Version-7 data [Wentz, 2013], which are available for the time period 1987-2013 and are at ~25 km spatial resolution.

Figure 4 shows the trend in total precipitable water from SSM/I for AMJ. The trends measured by SSM/I alternate from negative in April to positive in June but these changes are small and insignificant for all but a few isolated areas. Precipitable water trends over the GOM from NARR disagree with SSM/I however, and show significant reductions in all three months (not shown). Given the direct impact that GOM moisture plays on weather systems across the central United States, resolving this apparent discrepancy in summertime precipitable water trends between NARR and SSM/I is an important question, but beyond the scope of this article. Regardless, there is not a clear positive trend in any of the months of interest, when contrasted with the findings in Dirmeyer and Kinter [2010], which showed that changes in source moisture and rainfall over the Great Plains are positively correlated.

While there is uncertainty in GOM vapor trends, the increase in Central/Northern Plains rainfall is most likely explained by a more favorable dynamical environment for
thunderstorm development provided by low-level convergence in the GPLLJ exit region and upper-level lifting associated with the jet stream, both of which have intensified and migrated northward [see also Wang et al., 2013]. It should be noted that a reduction in source moisture of the GPLLJ might be partially compensated by evaporated irrigation water from agricultural activities [DeAngelis et al., 2010]; such an explanation requires further analysis.

4. Summary and Discussion

Analysis of NARR indicates notable increases in both the strength and northern extension of the GPLLJ for AMJ. There are concurrent changes in precipitation that vary by month but show common increases north of 40°N in the total amounts, frequency and intensity. Meanwhile, substantial decreases in total precipitation are evident south of 40°N, with consistent reductions in both frequency and intensity of rainfall. In addition to the increased strength and extent of the GPLLJ, there has been a concurrent northward shift of the upper level jet stream, i.e. 200-mb u-wind during May (not shown). The upper level jet stream provides synoptic support for the development and maintenance of thunderstorms, and its northward migration coupled with increased extent of the GPLLJ helps maintains synoptic lift [Wang et al., 2013], hence enhancing precipitation towards the Northern Plains. However, the intensification of extreme precipitation events seen in June is not accompanied by any changes in the upper jet (not shown), but appears to be closely tied to increased strength of the GPLLJ alone; this suggests a possible role of the increase in source moisture over the GOM in June. A modest decrease in moisture from the source region is found in April and May, but these changes do not have a consistent
impact on precipitation further inland. The ambiguity of these contrasting observations is further compounded by the fact that model and satellite datasets sometimes disagree on the sign of the vapor trend over the GOM. Thus, the observed changes in the precipitation characteristics (i.e., amount, frequency, and intensity) appear to be predominantly controlled by the observed change in atmospheric circulations, especially the GPLLJ.

The trends in the GPLLJ and precipitation reported here are supportive of previous findings in observations as well as future projections based on modeling studies. Cook et al. [2008] predicted that increases in greenhouse gases would result in an intensification of the GPLLJ, higher rainfall in the northern Great Plains, and reduced precipitation in the southern Great Plains. Wang et al. [2013] reported that the coupling between the GPLLJ and upper-level trough system has intensified during AMJ since 1979. In contrast, previous studies found evidence of the impacts of decadal climate oscillations in the Pacific and the Atlantic on the GPLLJ [Weaver et al., 2009; Nigam et al., 2011], as well as multidecadal influences on GPLLJ-related processes [Weaver et al., 2012]. With the limited temporal domain of NARR, decadal to multidecadal processes cannot be ruled out. Nonetheless, there is still the possibility that predicted changes in the GPLLJ and associated precipitation [Cook et al., 2008] are already underway.

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Figure 3-1. (a) EOF 2 of precipitation climatology for Central United States. White box highlights center of action, and is used for calculations for Fig 1c. (b) PC2 of precipitation climatology for Cent. U.S., showing the springtime peak of rainfall for the region. (c) Climatology of average pentad precipitation within the box in Fig 1a. Red bars are for the period 1979-1995, blue bars are for the period 1996-2012. Yellow line indicates percent difference between the two time periods.
Figure 3-2. Longitude-time Hovmöller diagrams, averaged over latitudes 32°N-37°N. Contour lines show 925mb v-wind magnitude (i.e. location of GPLJJ core), 10-30 m/s in 5 m/s intervals.
**Figure 3-3.** (a) Monthly climatology for precipitation (shaded) and 925mv wind field (vectors) and Latitude-time Hovmöller trend plots for (b) 925mb v-wind, (c) monthly total precipitation, (d) precipitation frequency and (e) frequency of extreme precipitation events, averaged along the longitude range indicated by the white boxes within monthly climatology plots. Thick bars along latitude axis on trend plots indicate latitudes for which regression coefficients are statistically significant at 95% confidence.
Figure 3-4. Linear regressions (1987-2012) of column-integrated water vapor over the Gulf of Mexico for SSM/I (a-c) and for NARR (d-f). Units are mm/year. Stippling indicates statistical significance at 95% confidence.
CHAPTER 4
A 140-YEAR GRIDDED SNOW WATER EQUIVALENT RECONSTRUCTION FOR UTAH BASED ON FOREST INVENTORY AND ANALYSIS (FIA) TREE-RING DATA

ABSTRACT

Observational data in the Intermountain West are sparse and short, and therefore are difficult for use in depicting past climate variability and extremes. This study presents the first reconstruction of April 1 snow water equivalent (SWE) using increment cores collected by the U.S. Forest Service Forest Inventory and Analysis Program (FIA) for the period of 1850-1989. In the state of Utah, SWE was reconstructed from 38 snow courses using a combination of detrended and standardized tree-ring indices derived from both FIA cores and classic chronologies. The results showed a significant correlation with observed SWE as well as statewide coherent variability on inter-annual to inter-decadal time scales. The extended period of record and high resolution of this SWE reconstruction provide further means for understanding water resources in Utah.

1. Introduction

Water supplies in the Intermountain West will be affected by a decrease in snowpack compounded by an amplified fluctuation of snowpack variability (Serreze et al., 1999; Stewart et al., 2005; Nash and Gleick, 1991; Barnett et al., 2005; Wise, 2012; Woodbury et al., 2012); this also includes Utah (Gillies et al., 2012). However, a relatively short period of instrumental record in the western United States limits
understanding of snowpack variability. Tree-ring width has long been used as a proxy for climate variability. In the western U.S., tree rings have been used to create a broad range of climate reconstructions including precipitation (e.g., Knight et al., 2010; Gray et al., 2004), temperature (e.g., Briffa et al., 1992), and streamflow (e.g., Carson and Munroe, 2005; Woodhouse and Lukas, 2006; Bekker et al., 2014). Mountain snowpack has also been reconstructed for parts of the Rocky Mountains (Woodhouse, 2003; Timilsena and Peichota, 2008; Pederson et al., 2011; Anderson et al., 2012).

There have been efforts to create gridded datasets with a broad spatial coverage using tree-ring chronologies, notably for temperature and precipitation (Fritts, 1991) and the Palmer Drought Severity Index (PDSI, Cook et al., 2004). These gridded products have proven to be useful for the analysis of long-term climate variability at regional to continental scales. These gridded data sets are limited, however, when it comes to analyzing watershed-scale variability within complex terrain such as Utah (see Fig. 1).

As was noted by DeRose et al. (2013) there is a gap in the coverage of International Tree-Rind Database (ITRDB) chronologies in the Utah region compared to others in the western U.S., and development of sufficient chronologies to enable fine-scale and broad-coverage reconstructions is cost-prohibitive. DeRose et al. (2013) developed increment cores collected by the U.S. Forest Service Forest Inventory and Analysis (FIA) program as an alternative tool for climate reconstructions. The FIA monitors and characterizes the Nation’s forest resources by adopting a high-density sampling strategy (see Section 2a). The FIA sampling strategy resulted in the collection of increment cores on a geographically unbiased grid at approximately 5km spacing throughout portions of the Interior West, including Utah.
The feasibility of the FIA tree-ring dataset in depicting climate variability has been established; DeRose et al. (2013) showed that the FIA tree-ring data in Utah had significant correlation with water year (Aug-Jul) precipitation, particularly over the mountain ranges. It is reasonable to assume that FIA tree-ring data can capture snowpack or SWE variability as well. Therefore, we have developed a reconstruction of April 1st snow water equivalent (SWE) for the state of Utah using the FIA data combined with traditionally developed chronologies (Fig. 1).

2. Data and methods

a) Tree-ring data

At each FIA collection location a suite of measurements are made periodically in order to characterize forest attributes and change over time (McRoberts et al., 2005; Smith, 2002). As part of the Interior West FIA program, increment cores were collected from a subset of trees on each plot to establish plot ages and growth rates. These trees represent the dominant species on the plot in terms of size and forest type. Because increment cores were sampled to represent dominant forest types, many tree species are represented in the FIA tree-ring data set. For this study, we used cores collected from Douglas-fir (DF, *Psuedotsuga menziessii* var. *glauc*a), ponderosa pine (PP, *Pinus ponderosa*), and common piñon (PE, *Pinus edulis* Engelm.), all of which grow at relatively low elevation and are known to be possible proxies for moisture availability. These species are potentially susceptible to drought and have been shown to be appropriate for use as climate proxies (e.g., Watson and Luckman, 2002; Gray et al.,
The FIA increment cores were subsequently measured and crossdated, and each time series was then detrended and standardized (e.g. Fritts, 1976; Fritts et al., 1979; see details in DeRose et al., 2013). Measuring and crossdating of FIA increment cores is ongoing; as of this writing, 2950 samples from locations in Utah, Colorado, Idaho, Wyoming and Montana have been processed. In our region of interest (36.5-43.5 N, 114.5-107.5 W) there were a total of 967 FIA samples.

The FIA tree-ring ring-width indices were supplemented by 31 standard chronologies from ITRDB and 31 additional standard chronologies developed by the Wasatch Dendroclimatology Research group (WADR, Rittenour et al., 2012). These chronologies were developed from DF, PE, PP and Rocky Mountain Juniper (*Juniperus scopulorum*) and have been used in reconstructions of streamflow for the Logan River (Allen et al., 2013) and Weber River (Bekker et al., 2014), and of Great Salt Lake (GSL) water level (DeRose et al., 2014). The WADR chronologies in particular provide added sample depth for northern Utah, where FIA samples of the desired species were sparse (Fig 1). FIA data is provided to the public at http://cliserv.jql.usu.edu/FIAdata/

**b) Instrumental data**

SWE observations from a total of 38 snow courses were obtained from the U.S. Department of Agriculture’s Natural Resources Conservation Service (http://www.wcc.nrcs.usda.gov/snow/, course names listed in Table 1, locations in Fig. 1). Locations were selected that had a period of record covering 1930-1989. All courses selected had no more than 10% of the record with no observations (i.e. 6 or fewer missing values). Many of these courses have longer records, but most FIA collections in Utah
were conducted in 1989, so a later date for the calibration period could not be used. Details of snow course data and their collection can be found at http://www.wcc.nrcs.usda.gov/factpub/sect_4a.html. SNOTEL data were not used due to the insufficient temporal coverage (post-1979) for this network.

c) Reconstruction Method

For each snow course, FIA and other chronology data (both current year and lagged 1 year) were tested as potential predictors using correlation analysis. The chronologies/trees with the highest correlations were then used in a multiple linear regression model, of the form

\[ Y = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k + \epsilon \]

built stepwise by adding predictors one at a time, to a maximum of 12 predictors. The predictive potential of each model was tested using the predictive error sum of squares (PRESS; Allen, 1974), a leave-one-out validation method taking the form

\[ PRESS = \sum_{i=1}^{n} (Y_i - \hat{Y}_{i-1})^2 \]

where \( n \)=number of observations, \( Y_i \) is the \( i \)th observation, and \( \hat{Y}_{i-1} \) is the predicted value of \( Y_i \) when \( Y_i \) was excluded from the regression. For each snow course the regression model with the smallest PRESS was selected as the final model.
3. Results

a) Calibration and Model Validation

In addition to reporting variance explained \( R^2 \), we also report adjusted \( R^2 \), calculated as

\[
R_{adj}^2 = R^2 - (1 - R^2) \frac{k}{n - k - 1}
\]

where \( n \) = sample size and \( k \) = number of predictors. This test penalizes the addition of predictors and thus reduces the inflation of \( R^2 \) due simply to additional regression parameters (Srivastava and Ullat, 1995). We also used a cross-validated \( R^2 \) based on the PRESS statistic

\[
R_{cv}^2 = 1 - \frac{PRESS}{TSS} = 1 - \frac{\sum_{i=1}^{n} (Y_i - \hat{Y}_{i,-1})^2}{\sum_{i=1}^{n} (Y_i - \overline{Y})^2}
\]

In the case of bad predictive models, \( R_{cv}^2 \) can take negative values if PRESS is greater than TSS, which means that the model predictions are worse than using the observational mean (Todeschini, 2007). Table 1 shows the \( R^2 \), number of predictors, \( R_{adj}^2 \) and \( R_{cv}^2 \) over the calibration period (1930-1989) for each reconstruction of the 38 snow courses used.

b) Gridded Interpolation

Next, the reconstructed SWE was interpolated to a regular rectangular grid. Such a grid extends the usefulness of data by enabling the integration of SWE estimates over space, thereby making estimates of total snowpack water content over a region. Gridded SWE datasets have been created before via ground observations (Brown et al., 2002) and satellite measurements (Brodzik and Armstrong, 2013), nonetheless these are less
common than other gridded climate variables such as temperature and precipitation and have limited temporal coverage (post-1978)

The combined snow course reconstructions were interpolated to a regular grid using Cressman objective analysis (Cressman, 1959; Jiang et al., 2009) to 4 km resolution, similar to the grid spacing used by PRISM dataset (Daly et al., 1994). Cressman analysis uses an iterative process of considering station data within successively smaller radii of influence to determine the interpolated value. We used four radii of influence: 3°, 2°, 1°, and ½° for our grids. A data mask was applied to any grid points with an elevation below 1800 m (~6000 ft.), where there is generally not a large snowpack accumulation compared to higher elevations.

One assumption using Cressman analysis is that the data being interpolated has spatial and temporal stationary; however, this assumption might not hold true with our data. To address the potential for spatial non-stationarity we added dummy observations in our region of interest filled with zeroes, essentially zero-padding the data. We accomplished this by adding 250 locations, which were assigned using a random number generator, provided that the locations were at least 75 km from any snow course location, which yields a density of dummy locations that is similar to the density and distribution of the snow courses themselves (see Fig. 2). We note that this zero-padding approach is intended only to minimize extrapolation problems at the edges of the domain, and is not necessarily an assumption that the point is actually snow-free.

Cressman analysis also does not account for orography in the gridding process, but snow accumulation is strongly related to elevation. Fig. 3 is a plot of SWE...
observations in Utah with respect to elevation, and illustrates this relationship. In order to account for orography, we adjusted the grid point values using

\[ SWE_{adj} = SWE + (0.188 \times (E_g - E_{ref})) \]

where \( E_g \) = elevation of grid point and \( E_{ref} \) = average elevation of snow courses used in the reconstruction. Fig. 4a shows the R\(^2\) between the reconstruction and observation grids. Almost the entire grid scores above 0.4, with particular skill shown in the southern and central Wastach and central Uinta mountains. This is consistent with results in DeRose et al. (2013), in which water-year precipitation correlated with FIA tree-ring data highest in the same mountain regions.

To further demonstrate the value of the FIA data in these reconstructions we replicated our methodology using only the ITRDB and WADR tree-ring chronologies. The resulting gridded reconstruction (Fig. 4b) showed reduced variance explained throughout the study area.

c) EOF analysis

A further investigation into the reconstruction was provided by empirical orthogonal function (EOF) analysis, which shows the major modes of variability in space and time in a dataset. Figs. 5b and 5e depict the first two leading modes of variability, which together explain over 95% of the total variance. EOF 1 shows statewide coherent variability in SWE, and is by far the largest mode of variability (~87%). EOF 2 shows a northwest-southeast dipole, a much weaker mode (~9%). This second mode is consistent with El Niño/Southern Oscillation (ENSO)-driven variability both in terms of spatial patterns and the relatively weak loading and low percentage of variance explained, since
Utah lies along the fulcrum of the regional-scale, north-south ENSO dipole (Wang et al., 2009; Mo, 2010; Wise, 2010; Brown, 2011). This is consistent with EOF 1 of tree-ring-derived PDSI (Cook et al. 2004) (Fig. 5a), which exhibits a regional center in Utah, and EOF 2 (Fig. 5e), which shows a wet/dry division across Utah. Additionally, the principle component time series for both our reconstruction and that of Cook et al. (2004) are significantly correlated ($p < 0.01$), particularly the first principle component (PC; Figs. 5c,g). This suggests that the gridded SWE data in Utah are broadly consistent with coarse-scale drought variability at the regional scale.

To examine whether the SWE reconstruction reflects the prominent drought variations that have been documented in the aforementioned studies, we examined the spectral properties of the PCs (Figs. 5d, h). PC1 shows significant periodicity at 16-40 year frequencies while PC 2 varies significantly at 4, 12 and ~50-year frequencies. The periodicity seen in PC 1 is consistent with the quasi-decadal variability recorded by the PDSI in Utah (Wang et al., 2009) and GSL levels (Wang et al., 2010), proposed to be caused by a teleconnection excited during the transitional phases of the Pacific quasi-decadal oscillation (QDO). Previous research on GSL levels (Lall and Mann, 1995; Wang et al., 2012) also found a teleconnection with the Interdecadal Pacific Oscillation (IPO), which occurs on a ~30-year frequency, coincident with the multidecadal variability found in PC 1 and the observation of Herweijer et al. (2007).

To examine further, we used the IPO index low-pass filtered at 4 years to eliminate high-frequency noise, to perform lagged correlation analysis (Fig. 6) on the PCs. IPO was chosen since it measures pan-Pacific tropical SST anomalies (Schubert et al., 2004a) that represent both inter-annual events (i.e. ENSO) as well as the decadal to
multidecadal variability such as QDO and IPO. The results show that PC 1 has significant 
\( p<0.01 \) correlation at a lag of 6 years, consistent with the transition-phase 
teleconnection noted by Wang et al. (2012), while PC 2 has the highest correlation at a 
lag of 1 year, in line with ENSO-related forcing.

A further note of interest, even though PC 1 has a much stronger effect than PC 2, 
when both occur simultaneously such as in 1934 (Figs. 5c, g), the reduction in SWE can 
be severe. Year 1934 was one of the strongest regional drought years in Utah which 
coincided with the Dust Bowl era, suggesting that ENSO forcing can be modulated by the 
larger-scale and stronger effects linked with PC 1 or the Pacific QDO’s transition phases, 
as was the case proposed for the Dust Bowl (Schubert et al., 2004b) and record floods in 
northern Utah (Wang et al., 2010) and in the Missouri River Basin (Wang et al., 2014).

4. Conclusions

We showed that the FIA tree-ring data are suitable as a predictor for SWE, at least 
for the state of Utah, given their broad depiction of water-year precipitation as was 
reported in DeRose et al. (2013). Using this knowledge, we produced a high-resolution 
(4 km) mountain snowpack reconstruction for Utah that more than doubles the temporal 
coverage available from instrumental records. It was demonstrated that a combination of 
FIA and classical chronologies skillfully reproduces SWE and calibrates well over the 
period of 1930-1989. Analysis of the 140-year reconstruction revealed significant 
variability at decadal time scales, which is consistent with prior studies investigating 
precipitation and drought variabilities in the Intermountain West based upon in-situ and 
tree-ring records. Primary modes of variability indicate that statewide SWE variability in
Utah is pronouncedly driven by decadal to multidecadal variability, while previous studies have shown one of the forcing sources as tropical Pacific SSTs during their respective phases of lifecycle.

The gridded FIA tree-ring dataset represents a useful source of past climate information at watershed level for water resource management. Observational data in the Intermountain West are sparse and have limited temporal coverage at primarily low elevations (except the more recent SNOTEL), and therefore are difficult for use in depicting past climate extremes. Because the understanding of historical controls on snowpack variability provides insight into snowpack conditions, any extended record of SWE like the one presented here with a long record can shed light on water availability and climate change impacts in the region.

Acknowledgements. Data is provided to the public at http://cliserv.jql.usu.edu/FIAdata/. Funding for this study came from the U.S. Dept. of the Interior’s WaterSMART Initiative R13AC80039, and the Utah State University Agricultural Experiment Station (#). Special thanks to the Wasatch Dendroclimatology Research group and the Utah State Dendro Lab for preparation of the FIA increment cores.

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Figure 4-1. Terrain in the state of Utah. Locations of various data types are marked with colored x’s (see legend). ITRDB and WADR sites are fully developed chronologies, FIA markers are locations of individual tree increment cores.
Figure 4-2. Sample plot of regridded April 1 SWE. Red points indicate locations of snow courses, green points indicate locations of dummy observations used for spatial zero padding prior to Cressman interpolation.
Figure 4-3. Plot of April 1 SWE vs. elevation in Utah. Bold black points show mean value for each snow course, and grey points show individual measurements. Solid line is linear regression of mean snow course values with respect to elevation; regression function shown in top left.
Figure 4-4. Point-to-point $R^2$ map of reconstructed to observed April 1 SWE, (a) including and (b) excluding FIA data.
Figure 4-5. (a) EOF 1 for NADA (b) EOF 1 for FIA (c) PC (solid: FIA, dashed: NADA) and (d) spectral power of PC of reconstructed SWE. In (d), red line depicts red noise spectrum, dashed line shows red noise exceedance at 95% confidence. (e)-(h) Same as (a)-(d) but for EOF 2 and PC 2.
Figure 4-6. Lagged correlation of PCs with 4-yr low-pass filtered IPO. Dashed lines denote significant correlation at 95% and 99% confidence.
Table 4-1. Summary statistics for snow course reconstructions

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CHAPTER 5
EVALUATION OF LONG-TERM FORECAST POTENTIAL USING CMIP5
DECADAL PREDICTION EXPERIMENTS

ABSTRACT

CMIP5 decadal experiments offer the possibility of extended-range predictions of global climate in the near future. Sea surface temperature (SST) variability provides an ideal test for this concept. We test Pacific Decadal Oscillation (PDO) and Atlantic Multidecadal Oscillation (AMO) projections from decadal prediction experiments of 10-year length initialized every five years from 1960 to 2005. These tests are conducted within the context of climate events such as the global warming hiatus and changing precipitation regimes in the state of Utah. We also check for improvement of forecast skill for contemporary vs. early initializations as observational data used as initial conditions improve. Additionally, we consider forecast skill for PDO and AMO when these ocean states change regime. Ensembles of all available models are considered, as well as ensembles comprised of individual models that exhibit the highest forecast skill for each index. Projections for future SST anomalies are presented using 30-year experiments initialized in 2005. Analysis shows that model ensembles exhibit useful skill in prediction of global average temperature trends, but fail to adequately capture regime shifts in PDO and AMO. Initialization data are shown to have a greater effect on PDO forecast than AMO. Additionally, regime changes in both AMO and PDO do not seem to have a consistent effect on forecast skill.
1. Introduction

Even as weather and climate predictions have evolved into powerful prognostic tools, the window of prediction is still relatively narrow, with the seasonal or annual scale being the outer limit of operational prediction models. However, Earth’s climate fluctuates on much longer time-scales. Processes such as the Pacific Decadal Oscillation (PDO; Mantua et al., 1997) and the Atlantic Multidecadal Oscillation (AMO; Enfield et al., 2001) have large effects on global climate over decadal time-scales and can bring about prolonged events such as the Dust Bowl of the 1930s (Schubert et al., 2004).

a. The Pacific decadal oscillation

The PDO is an interdecadal mode of SST variability in the extratropical North Pacific Ocean that has been implicated in a variety of climatological and ecological impacts (Mantua et al., 1997; Francis and Hare, 1998; Mantua and Hare, 2002). It is defined as the first leading EOF mode of monthly SST anomalies in the North Pacific Ocean (poleward of 20° N, see Fig. 1). The positive(negative) phase is characterized by cold(warm) anomalies extending east from Japan out into the central Pacific, and a horseshoe-shaped area of warm(cold) anomalies along the west coast of North America. Spectral analysis has revealed dominant periodicities at 15-25 and 50-70 year frequencies (Minobe, 1999; Chao, 2000).

There are differing schools of thought regarding the underlying dynamics of the PDO. One suggests that extratropical atmospheric response to El Niño forcing results in changes in the strength of the subtropical high, which leads to altered surface fluxes over
the central North Pacific (Nakamura et al., 1997; Alexander et al., 2002); this behavior can be modeled using an autoregressive (AR1) regression model (Newman et al., 2003). Changes in the strength and position of the Aleutian low and resultant changes in surface wind stress and Eckman transport have also been suggested as a possible source of forcing for the PDO (Latif and Barnett, 1994; Nakamura et al., 1997). Schneider and Cornuelle (2005) showed that an autoregressive model using both these forcing sources resulted in a successful reconstruction of PDO.

The PDO forces climate anomalies in North America are similar in many respects to that of El Niño forcing, but are usually less intense (Mantua and Hare, 2002; Latif and Barnett, 1996). During positive (negative) phases warm (cool) surface temperature anomalies occur in the Pacific Northwest, British Columbia and Alaska, while cool (warm) anomalies occur in the southeast U.S. and Mexico. Reduced (increased) precipitation falls in the Pacific Northwest and Appalachians while wet (dry) anomalies occur in the southwest and southeast U.S., and along the Alaskan coast. It has also been suggested that PDO modulates El Niño teleconnections, with stronger response occurring when PDO and El Niño are in phase (Gershunov and Barnett, 1998).

b. The Atlantic multidecadal oscillation

Like the PDO, the AMO is a long-lived mode of SST variability that occurs in the North Atlantic Ocean. It is characterized by warm (cool) SST anomalies in the North Atlantic Ocean, especially off the coast of Newfoundland and Greenland during the positive (negative) phase of the AMO. Current understanding of AMO mechanisms is based on modeling studies, which suggest variations in thermohaline circulation in the
Atlantic as the driver for the evolution of SST anomalies in the North Atlantic (Delworth and Mann, 2000; Knight et al., 2005).

There are several methods for defining the AMO. Some definitions average North Atlantic SST anomalies after removing any linear trend, with differing methods for removing the trend or area to consider (Trenberth and Shea, 2005; van Oldenborgh et al., 2009). Others have used EOF analysis, similar to PDO definitions (Ting et al., 2009; Guan and Nigam, 2009). These various definitions result in similar indices, with dominant periodicity in the 40-70-year range.

The AMO has been tied to a variety of climate teleconnections, including Atlantic hurricane activity (Goldenberg et al., 2001), and rainfall over Northeast Brazil (Folland et al., 2001) and the Sahel region (Knight et al., 2006). As well as these tropical influences, the AMO has extratropical climate teleconnections, influencing precipitation patterns over Europe and North America (Knight et al., 2006). The AMO can act independently as a forcing factor in global climate, and has also been shown to have an interactive effect with the PDO on North American climate (McCabe et al., 2003).

c. AMO/PDO teleconnections

Long-lived ocean oscillations such as the AMO and PDO can have a prolonged impact on global climate. It has been proposed that one such example of this kind of interaction is the so-called warming hiatus (see below), which has gotten a great deal of attention in recent years and has been the subject of intense scrutiny. There have been questions as to whether the hiatus is actually a real phenomenon, not only in the popular press, but among the scientific community as well. Radiation budget studies show that
the net radiation budget at the top of the atmosphere has not changed significantly (Trenberth and Fasullo, 2010; Trenberth et al., 2014). Additionally, estimates of total ocean heat content show a steady increase in ocean heat since at least the 1970s (Nuccitelli et al., 2013; Abraham et al., 2013). Furthermore, statistical analysis of global surface temperature (T_{glob}) shows little evidence of a hiatus. Cahill et al. (2015) showed that warming trend rates changed at 1912, 1940, and 1970, but did not find a similar rate of change in recent years.

While the evidence for a change in warming rate is questionable, the lower atmosphere is a small thermal sink, and is subject to internal variability on a large range of timescales. Decadal-scale variability is readily apparent in T_{glob}, which has been attributed to the AMO (Liu, 2012), and more prominently, to the PDO/Interdecadal Pacific Oscillation (IPO; Meehl et al., 2011, 2013; Dai et al., 1015). Meehl et al. (2011, 2013) showed through modeling studies that sub-surface ocean heat storage is enhanced and global temperature trends are reduced during the negative phase of the IPO, by modifying ocean-mixing processes.

In addition to global effects (i.e., T_{glob}), these long-lived oscillations have effects at regional scales. It is known that precipitation in the western U.S. is modulated by the PDO (Gutzler et al., 2002) and the AMO (Enfield, 2011), and so skillful prediction of these indices would be of great value water resource managers by promising the prospect of anticipating long-term drought or pluvial periods.

Unforced CMIP5 model runs show IPO as a leading inducer of decadal-scale T_{glob} variability (Maher et al., 2014; Brown et al., 2015). Imposing observational sea surface temperatures (SST) of the tropical Eastern Pacific only in a coupled ocean-atmosphere
model resulted in a warming hiatus in the model very similar to the instrumental record (Kosaka and Xie, 2013). Models therefore are capable of capturing both the IPO and its effects on global temperature, and offer the potential for predictability of decadal-scale events such as the recent warming hiatus. Climate models are not as skillful when it comes to reproducing the response of regional precipitation in the western U.S. to PDO forcing (Smith et al., 2015), so anticipation of event-specific precipitation response is probably still beyond reach, but prediction of SST anomalies themselves is nonetheless a valuable tool when it comes to regional planning.

We therefore have assessed the CMIP5 decadal prediction experiments’ performance in anticipating the recent warming hiatus and long-lived precipitation regimes in the western U.S., specifically in the state of Utah. We chose to focus on Utah both as a matter of our prior interest in the region, and because previous research has demonstrated sensitivity of this region’s precipitation to decadal-scale forcing from both the Pacific and Atlantic Oceans (Gutzler et al., 2002; Enfield, 2011; Wang et al., 2012). The decadal experiments were designed to test the capability of current climate models to offer climate prediction at longer time scales, and thus offer an ideal testbed for assessing if current models are capable of anticipating events such as the warming hiatus, transitions in regional precipitation, or changes in ocean temperature regimes such as the PDO or AMO.

2. Data

The observational SST data used in this study are the NOAA Extended Reconstructed Sea Surface Temperature v4 (ERSST; Huang et al., 2015). Observational
surface air temperatures were provided by the National Center for Environmental Prediction (NCEP)/National Center for Atmospheric Research (NCAR) reanalysis 1 (NCEP1; Kalnay et al., 1996). For observational precipitation we used the University of East Anglia Climatic Research Unit (CRU) gridded precipitation dataset v.3.22 (Harris et al., 2013).

To be included in our study, CMIP5 models were required to have surface air temperature and total precipitation available for decadal experiments starting in 1960 and every fifth year afterwards. Additionally, for the experiment starting in 2005 the output had to extend to 2035. 12 models satisfied these criteria, and are listed in Table 1, along with citing information for the model. Sea surface temperature data was not used due to general unavailability of this variable at the time the data were accessed.

3. Methods

In the absence of model SST output, an alternate method for calculation of the SST-based PDO and AMO indices was required. We therefore developed and tested indices based on surface air temperature. For both the PDO and AMO we started with the leading EOF for the appropriate domain (Pacific: 20-70N, 125E-100W, see Fig. 1; Atlantic: 20S-65N, 75W-0E, see Fig. 2). Using the loading pattern as guidance we then selected a box that encompasses the center of action (Pacific: 30N-45N, 155E-150W; Atlantic: 5N-65N, 55W-5W). Monthly surface air temperature anomalies were then area-averaged within these boxes and standardized by standard deviation to approximate the SST-based index. For the PDO the time series was also multiplied by -1, since the positive phase of the PDO results in negative anomalies in the center of action. These air
temperature-based indices proved to be strong estimates when compared with NOAA Climate Prediction Center-issued indices (PDO: $R^2 = 0.797$; AMO: $R^2 = 0.712$). For the purposes of this index testing monthly data were used, but for subsequent testing all indices were converted to yearly values to reduce signal noise associated with monthly data.

To assess individual model performance, we made an ensemble of PDO and AMO for all available initializations and start times to create a “first-look” for each model. Each ensemble was then scored by correlation with observed PDO and AMO. Those models that had a significant correlation ($>0.246$, df=44) were then selected to comprise a “skill” ensemble for the index in question. We also tested modeled vs. observed global average temperature ($T_{glb}$) and total annual precipitation in Utah ($P_{utah}$; 37N-42N, 114W-109W), both using the all-model ensemble and the AMO and PDO skill ensembles to evaluate modeled precipitation response to SST forcing. In time series plots both raw data and smoothed time series (treated with a cubic spline) are given. Statistical testing was performed using raw data; smoothed data is presented to help accentuate low frequency variability.

In addition to the merged ensemble that included members from all start times, we assessed forecast skill by lead-time, by considering only the first year of the model output for each initial time for forecast lead of 1 year, the second year for 2-year lead-time, etc. Thusly we could evaluate the decay of forecast skill in these long-range climate forecasts.

Another aspect of these forecasts we wished to evaluate was whether forecast skill improved with later initialization times. Initialization data for climate data, especially concerning ocean state, has improved due to increased density of observations, so this
evaluation seeks to test the importance of initial conditions for multiyear climate prediction. To accomplish this, we consider three-year prediction blocks (lead times 1-3 yr, 4-6 yr, and 7-9 yr) from three consecutive initialization periods, starting with 1960-1970 and continuing to 1995-2005.

Lastly, we viewed output from the long-range experiments initialized on 2005 observations and run out to 2035, to report long-term (i.e., multidecadal) forecasts for PDO, AMO and T_{glb} as generated from the ensembles listed above.

4. Results/Discussion

a. Testing for PDO/AMO forecast skill

Fig. 3 shows both observed and ensemble forecast PDO, both for a) an all-model and b) skill ensemble (consisting of CanCM4, CCSM4, FGOALS-s2 and IPSL-CM5A-LR), with individual models included as light thin lines. In both cases the prediction ensembles perform poorly, oscillating around zero and out of phase with observations. Neither ensemble captures the PDO regime change that occurred in 1977. However, starting in the mid-1980s the predicted PDO becomes phase-aligned with observed PDO, and both ensembles have a negative PDO post-1998, very much in agreement with observations. Also of note is although initially out of phase, the models exhibit decadal-scale oscillations of similar frequency to observed PDO, but fail to reproduce the longer multidecadal-scale changes, instead oscillating at decadal frequencies about zero.

Fig. 4 shows the results of the initialization tests for PDO. The bottom graph shows the correlation scores for each group of forecast lead times and initialization
periods, while the upper panel provides a smoothed time series of the PDO for reference. The first thing to note is the skill for forecast years 1-3. There is a steady increase in forecast skill as initialization time approaches the present, with the exception of the final group of initializations. Forecast years 4-6, by contrast, perform best during the 1980s, which then drops down to near-zero skill by the latest initializations. Forecast years 7-9 has a similar peak in skill during the 1980s and a drop-off in skill during later initialization periods. Unlike years 1-3 and 4-6, years 7-9 exhibit significant forecast skill during the earliest initialization periods. For all three groups of forecast periods correlations exceed significance tests at 95% confidence for at least two initialization periods, but not necessarily the same two.

Fig. 5 repeats Fig. 3, this time for AMO. Similar to the PDO testing, the models do well in capturing decadal-scale oscillations seen in observed AMO, but do not exhibit multidecadal variability. When comparing the all-model and skill ensembles (consisting of HadCM3 and MIROC5), there is a qualitative difference in depiction of AMO post-1996, during which observed AMO undergoes a regime change. A large number of models in the full ensemble initially mirror observations but quickly swing back into negative values, while the skill ensemble remains above zero post-1997.

Like Fig. 4, Fig. 6 presents results of initialization testing, this time for AMO. There are some noticeable differences in these results compared with the PDO tests. First, for the year 1-3 forecasts during early initializations forecast skill is highest, exceeding significance testing at 95% confidence. However, there is a reduction in skill as initialization times become closer to present. Second, forecast years 4-6 never achieve a skill that exceed 95% confidence in statistical significance, although it gets close during
the 1990-2000 group of initializations. Forecast years 7-9 do exceed that threshold during the 1980-1995 groups of initializations but otherwise exhibit little skill in forecasting the state of AMO.

One of our tests sought to examine the effects of initialization data on subsequent forecasts (Figs. 4 & 6), by comparing the forecast skill of early model initializations, when ocean data were sparse to later, when ocean data are much denser and thus give a better estimate of the ocean state. When we consider the PDO testing, there is a compelling case for the argument that this increase in data availability yields an increased forecast skill, particularly for the earliest set of forecast lead times. This theory is not supported by the same test when conducted for AMO however. It is certainly possible that since the two oscillations are the result of different processes within the ocean that such a comparison is not appropriate, but a definitive answer to this is beyond the scope of this study.

We can also consider a different question using the results from the initialization testing: can the decadal forecasts retain skill during periods when there is a regime change in either the PDO or AMO, or are they only capable of good forecasts during a stable regime (i.e., persistence forecasting)? The result from the PDO testing shows that some of the highest skill for the models’ forecasts occur during a regime change from positive to negative PDO during the early 1990s. This, when considered in tandem with the improved skill we attribute to initialization implies that the models show promise in successful forecasting of regime changes given an accurate initial state, at least for PDO. The result from the AMO tests however presents a different picture. During the experimental period the AMO changes regimes once, right around 1990. This is
concurrent with a drop in forecast skill for both the 1-3 and 4-6 forecast years, thus implying that the model performs better during stable regimes and has difficulty anticipating a regime change, at least when considering the AMO.

b. Modeled response to PDO/AMO forcing

The CMIP5 models generally do well in reproducing $T_{glb}$, regardless of whether we consider the all-model ensemble or the skill ensembles. As is seen in the Taylor diagram in Fig. 7 (Taylor, 2001), all three ensembles achieve correlations with observed $T_{glb}$ over 0.9 for all forecast lead times, with the exception of the 2-year forecast from the PDO ensemble. All ensembles show reduced amplitude of variance about the mean when compared with observations, again without one ensemble performing meaningfully better than the others.

In contrast, modeled $P_{utah}$ testing (Fig. 8) indicates that CMIP5 models have difficulty in prediction of precipitation in Utah. Ensembles rarely correlate above 0.3 for all forecast lead times, although variance ratios with observations are closer to 1 than for $T_{glb}$. If we consider time series plots for modeled $P_{utah}$ (Fig. 9), we see the all-models ensemble (Fig. 9a) is frequently out of phase with decadal- and multidecadal scale variability in observed precipitation. The PDO skill ensemble (Fig. 9b) has similar phasing problems, and does not exhibit much variability at decadal and multidecadal time scales. This lack of long-period variability is also seen with the AMO skill ensemble (Fig. 9c). Both the all-model and AMO skill ensembles exhibit a downward trend in annual precipitation, although this trend reverses at the end of the analysis period for the all-model ensemble.
The results seen in our investigation reveal a mixed bag when it comes to the possibility of operational decadal-scale climate prediction. On one hand, the models do very well in anticipating changes in $T_{\text{gbl}}$, ($r>0.9$), including such details as the increased warming rate in the 1990s and the slowdown in warming post 2000. Furthermore, current climate models are able to generate internal decadal-scale variability in SSTs such as PDO and AMO. However, they fail to reproduce the resulting teleconnections (Smith et al., 2015), and our study shows they have difficulty in phasing such variability with similar changes seen in observed datasets.

The lack of multidecadal variability seen in the 1960-2005 tests may be a result of our testing protocol. For this portion of the testing we simply averaged all available forecasts, regardless of initialization time into one-time series. This has the potential to flatten out the overall time series, due to lumping together models that have been running long enough to start exhibiting decadal variability with others that are still spinning up and have not begun to generate internal dynamic changes and responses.

The long (30-year, beginning 2005) experiments exhibit realistic low-frequency variability for both PDO and AMO. However, similarly to earlier analysis there are some phasing problems, especially with PDO. The all-ensembles PDO (Fig. 10a) shows a steady decline and transition to a negative phase, while the PDO skill ensemble flattens out after reaching neutral conditions post-2010. Observed PDO, starting in 2005, was initially negative but has swung upward in recent years in an apparent switch into a warm phase (CPC report; http://www.cpc.ncep.noaa.gov/products/GODAS/ocean_briefing_gif/global_ocean_monitoring_2016_01.pdf). It remains to be seen whether this is the beginning of a warm phase,
or if the PDO will remain at a neutral phase, but nonetheless the decadal predictions failed to capture PDO behavior during the first 10 years of their simulations, and therefore are of questionable usefulness moving forward.

Modeled AMO for both ensembles (Fig. 11) indicate a transition from cold to warm phase somewhere around 2025 after a negative phase beginning near-present, which is consistent with recent research (McCarthy et al., 2015). The first ten years of simulation validate slightly better than the PDO tests, but earlier testing showed limited skill in capturing AMO variability, so like the PDO predictions, the AMO predictions are of questionable value.

5. Conclusions

We tested output from the CMIP5 decadal predictions for forecast skill of the PDO and AMO, as well as T_{glb} and P_{Utah} to assess the state of long-range climate prediction. We found mixed results, with strong forecast skill for T_{glb}, but much lower and generally unreliable forecast skill otherwise. We also specifically tested for initialization effects as well as for changes in forecast skill near regime changes of AMO and PDO, and found more mixed results, with initialization appearing to have a bigger effect on PDO forecast than that of AMO. Regime change forecast showed more promise for PDO than for AMO.

The questions that stem from these results represent some of the many challenges with analysis of the CMIP5 experiments: there are so many data available, spanning not only different models, but different model settings, initialization times, etc. In addition to the initialization question, there is also the potential for model spin-up to introduce
spurious trends to model output (Hobbs et al., 2016). Energy imbalance issues during spin-up described therein were shown to have a significant effect on ocean state and total ocean heat content, and thus could skew subsequent behavior within the model. It was also shown that there is potential to remove such a trend post-hoc; therefore, there is the possibility of improving forecast performance by taking this approach. Due to these factors, experimental design thus becomes very important and has the potential to influence the resulting analysis. Future work will further examine, modify and refine our experimental design to reduce the possibility of this potential flaw in analysis of the CMIP5 experiments.

References


Tables and Figures

**Table 5-1.** List of CMIP5 models used for analysis.

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<td>CCSM4</td>
<td>Gent et al. (2013)</td>
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<td>CNRM-CM5</td>
<td>Mignot and Bony (2013)</td>
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<td>FGOALS-g2</td>
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<td>FGOALS-s2</td>
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<td>Collins et al. (2001)</td>
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<td>IPSL-CM5A-LR</td>
<td>Mignot and Bony (2013)</td>
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<td>MIROC4H</td>
<td>Sakamoto et al. (2012)</td>
</tr>
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<td>MIROC5</td>
<td>Watanabe et al. (2010)</td>
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<td>MPI-ESM-LR</td>
<td>Giorgetta et al. (2013)</td>
</tr>
<tr>
<td>MRI-CGCM3</td>
<td>Yukimoto et al. (2012)</td>
</tr>
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Figure 5-1. (a) EOF1 for North Pacific Ocean, and (b) PC1, PDO index (as published by NOAA Climate Prediction Center), and surface temperature-based PDO index.
Figure 5-2. (a) EOF1 for North Atlantic Ocean, and (b) PC1, AMO index (as published by NOAA Climate Prediction Center), and surface temperature-based AMO index.
Figure 5-3. Observed PDO index shown with (a) all-model ensemble and (b) PDO-skill ensemble.
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Figure 5-8. Taylor diagram illustrating ensemble skill for $P_{\text{Utah}}$ prediction.
Figure 5-9. Observed $P_{\text{Utah}}$ index shown with (a) all-model ensemble and (b) PDO-skill ensemble and (c) AMO-skill ensemble.
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Figure 5-11. Observed AMO index shown with future projections for (a) all-model ensemble and (b) AMO-skill ensemble.
CHAPTER 6

CONCLUSIONS

The primary objective in this course of research was to use climate diagnostics to gain a better understanding of hydroclimate in a variety of climate regimes. There was a specific emphasis on development of tools with value towards effective management of water resources, with a secondary emphasis on research specific to Utah. This began with preliminary work to develop and test analytical tools; these efforts were detailed in Chapters 2 and 3.

Chapter 2 focused on natural climate variability in the context of the Sahel region of Africa, where we discovered a link between atmospheric circulation anomalies over the North Atlantic Ocean and changes in monsoonal rain over the Sahel. We also evaluated the Climate Forecast System global coupled model for performance in reproduction and forecasting of this relationship. We found that the model failed to reproduce the Atlantic Ocean-Sahel precipitation link, nor could it provide skillful predictions of circulation anomalies in the North Atlantic.

Long-term trends, a potential indicator of effects due to climate change, were the primary subject of Chapter 3. We conducted an analysis of changes in the behavior of the Great Plains low-level jet, a key feature in the spring precipitation regime of the region. We found that since 1979 the low-level jet has strengthened, which in turn has altered the timing and location of peak spring precipitation. This finding has important implications for regional agriculture, which relies on spring precipitation to help kick off the growing season.
The development of a tree-ring-based reconstruction of April 1 SWE for the state of Utah, highlighted in Chapter 4, was the strongest result towards the primary objective. This dataset has doubled the available record of Utah snowpack, a major source of available freshwater for the region, and provides better constraints on the range of variability for this important resource. Analysis of the reconstructed SWE shows the dominant mode of variability to be regionally coherent at quasi- to multi-decadal frequencies. This is consistent with previous research, which links Great Basin precipitation anomalies to the Pacific Quasi-decadal Oscillation and to PDO-ENSO coupling.

Since both the PDO and the AMO have been implicated as forcing factors in Great Basin precipitation and more broadly to global climate, the next objective was to test long-term predictability of these important modes of variability via CMIP5 decadal prediction experiments, discussed in Chapter 5. It was found that while current climate models exhibit skill in prediction of planetary-scale variability (e.g. global average temperature), it is beyond the capabilities of these models to successfully anticipate changes in PDO or AMO. While an undesirable result, such findings are an important step in model development. Our study provides a framework for evaluation of future developments in climate models, which may be capable in the future of capturing such SST modulation. Furthermore, the upward trend in global surface temperature, which the CMIP5 models indicate will continue, is mirrored by a concurrent decrease in the snow/rain ratio of winter precipitation in Utah. It is reasonable to assume that these concurrent trends are related, and have broad implications for the future of water management in the state.
Future work for this line of research includes extending the snowpack reconstruction further into the past, and possibly increasing spatial coverage of the dataset. This would improve constraints and recurrence intervals on extreme events, and also open the possibility of examining long-term behavior of climate interactions, such as the ENSO-dipole. Additionally, the development of the CMIP5 evaluation can lead to further investigation into the strengths and weaknesses of these experiments, as well as outlining a framework for working with not only the decadal prediction, but also other experiments which were a part of the CMIP5 design.
APPENDICES
APPENDIX A

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July 18, 2016

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Education

University of California, Santa Cruz: Master of Science, Earth Sciences (2011).
Master's thesis: Implications of Climate Change of Major Watersheds of the Western United States: a Modeling Investigation to 2070.

University of Northern Colorado: Bachelor of Science, Earth Sciences: meteorology emphasis (2009).

Academic Work Experience

Research Assistant (2012-present)
Conducted research that led to two publications on climate variability in sub-Saharan Africa and climate change-induced trends in precipitation trends over the U.S. Great Plains. Used tree-ring data collected from a U.S. Forest Service program to create snowpack reconstruction for state of Utah dating to 1850 (manuscript in revision). Produced numerous analyses and figures for academic advisor in support of various research topics. Also served as teaching assistant for PSC3820 Climate Change (Spring, '13 & '14) and was responsible for grading and assisting students with assignments in and out of class.

Research Assistant (2010-2011)
Analyzed model output produced at UCSC for the North American Regional Climate Change Assessment Program (NARCCAP) to evaluate the effects of climate change based on RCP4.5 emissions scenario on temperature, precipitation, and mountain snowpack in the Colorado, Colombia, and Sacramento-San Joaquin river basins.

Teaching Assistant (2010-2011)
Natural History of Dinosaurs (Spr. '10) Led paper discussions, assisted in grading and evaluation of students, managed communication between professor and students. Earth History and Climate Change (Fall, '10) Administered exams and assisted in grading and evaluation of students, assisted students on one-to-one basis in understanding of concepts presented in class.
Geology of National Parks (Spr. '11) In small discussion groups, lectured on concepts of
geology as related to themes presented in main lecture. Administered exams and maintained student grades.

Research Assistant (2009)
Responsible for creating a plant functional-type analysis and climatological overview of North America during the Eocene Epoch based on model output provided by academic advisor. Trained in use of Weather Research and Forecast (WRF) atmospheric model.

Professional Memberships
American Meteorological Society
American Geophysical Union

Specialized Training
Software Carpentry Workshop, USU, Logan UT (2012)

Journal Publications


Book Chapters


Presentations


White, K., Allen, N., Barandiaran, D., Endter-Wada, J., Gale, J., Kopp, K., Mesner, N., Rupp, L., Managing the drought – tools from USU. Six County Association of Governments Executive Committee Meeting, June 3, 2015.


Wang, S.-Y., Barandiaran, D., et al., 2014: Could U.S. extreme droughts have been
anticipated? - A NASA NEWS initiative on extremes. AMS 94th Annual Meeting, Atlanta, Georgia, February 2-6, 2014.


**Awards**

USU College of Agriculture and Applied Science Graduate Student Researcher of the Year, 2015.

Student Travel Grant, Climate Detection and Prediction Workshop, 2012 and 2013