Multimodel Estimates of Atmospheric Response to Modes of SST Variability and Implications for Droughts

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ABSTRACT

A set of idealized global model experiments was performed by several modeling centers as part of the Drought Working Group of the U.S. Climate Variability and Predictability component of the World Climate Research Programme (CLIVAR). The purpose of the experiments was to assess the role of the leading modes of sea surface temperature (SST) variability on the climate over the continents, with particular emphasis on the influence of SSTs on surface climate variability and droughts over the United States. An analysis based on several models gives more credibility to the results since it relies on the assessment of impacts that are robust across different models.

Coordinated atmospheric general circulation model (AGCM) simulations forced with three modes of SST variability were analyzed. The results show that the SST-forced precipitation variability over the central United States is dominated by the SST mode with maximum loading in the central Pacific Ocean. The SST mode with loading in the Atlantic Ocean, and a mode that is dominated by trends in SSTs, lead to a smaller response.

Based on the response to the idealized SSTs, the precipitation response for the twentieth century was also reconstructed. A comparison with the Atmospheric Model Intercomparison Project (AMIP) simulations forced with the observed SSTs illustrates that the reconstructed precipitation variability was similar to the one in the AMIP simulations, further supporting the conclusion that the SST modes identified in the present analysis play a dominant role in the precipitation variability over the United States. One notable exception is the Dust Bowl of the 1930s, and further analysis regarding this major climate extreme is discussed.

1. Introduction

Toward identifying the causal mechanism for the occurrences of long-term droughts, the Drought Working Group (DWG) of the U.S. Climate Variability and Predictability component of the World Climate Research Programme (CLIVAR) was formed in December 2006. The approach of the DWG was to coordinate evaluations of existing model simulations and to also coordinate new experiments designed to address some of the outstanding questions related to drought variability and predictability. Six modeling groups joined in the effort and produced a wealth of model simulation. The primary goal of the focused effort was to quantify the role of sea surface temperature (SST) variability in changes of the atmospheric circulation and terrestrial climate.

Various large-scale patterns of sea surface temperature (SST) variability have been known for many years. A dominant mode of SST variability is associated with the El Niño–Southern Oscillation (ENSO). Other well-known modes of SST variability include the Pacific decadal oscillation (PDO) for the northern Pacific (Mantua et al. 1997), the Interdecadal Pacific Oscillation (IPO) the basinwide pattern (Power et. 1999), the North Atlantic multidecadal oscillation (AMO) (Enfield et al. 2001), and the Indian Ocean dipole (IOD) (Saji et al. 1999). In addition to the quasiperiodic modes of SST variability, trends in the SSTs, for example, an upward trend in SSTs in all tropical ocean basins, have also been identified.

Modes of SST variability have also been linked to atmospheric and terrestrial climate variability over different regions of the globe. For example, changes in North Pacific SST have been associated with droughts in...
the western and central United States (Namais 1969, 1983). Long-term precipitation variability over the U.S. Great Plains has been linked to SST anomalies across a wide swath of the Pacific Ocean (Schubert et al. 2004a). Hoerling and Kumar (2003) identified the importance of SST anomalies outside of the tropical Pacific and demonstrated the role SSTs in the Indian Ocean have on the hydroclimate of the United States that also extends across a latitudinal belt in the Northern Hemisphere. More recently, the persistent La Niña that ranged from the late twentieth to the early twenty-first centuries has been linked to the multiyear drought of the western United States (Seager et al. 2005).

Leveraging on the set of coordinated atmospheric general circulation model (AGCM) simulations that were part of the DWG, the present analysis looks at the relationship between the leading patterns of SST variability and their influences on the climate over land areas. The analysis includes 1) the observed relationship of the trend and the Pacific and Atlantic modes of SST variability with precipitation and surface air temperature, 2) the influence of the modes of SST variability on the atmospheric and terrestrial climates in idealized AGCM simulations, and 3) the extent to which the variability in the AGCM simulations forced with observed SSTs [in the so-called Atmospheric Model Intercomparison Project (AMIP) simulations] can be reproduced based on the response inferred from the idealized AGCM simulations. For more information on the overview of the U.S. CLIVAR Drought Working Group, please see the overview paper by Schubert et al. (2009).

The identification of the leading patterns of SST variability is described in section 2. A description of the observed data and models used in the study is in section 3. The AGCM simulations are described in section 4. The results are presented in section 5, and section 6 contains the conclusions.

2. Identification of the leading modes of SST variability

A more in-depth description of the forcing patterns used in this study can be found in Schubert et al. (2009). The leading patterns of SST variability are identified based on a rotated empirical orthogonal function (REOF) analysis of the annual mean SSTs from version 1 of the Hadley Centre Sea Ice and Sea Surface Temperature (HadISST) data set (Rayner et al. 2003). The 15 leading EOFs were rotated using varimax rotation (Kaiser 1958). To avoid contamination of sea ice points, the analysis was restricted to grid points that were completely ice free for the years 1901–2004. The leading mode of variability in this analysis is the trend of global SSTs, which explains 27.2% of the annual mean SST variance. The second leading mode is an ENSO-like pattern and explains 20.5% of the variance. The third mode, which represents only 5.8% of the global variance, is a North Atlantic pattern, similar to the Atlantic multidecadal oscillation.

The spatial pattern of the leading REOF shows a fairly uniform loading throughout the world’s oceans (Fig. 1). The highest loading occurs in the southern Indian Ocean, and there is a noticeable minimum in the central tropical Pacific Ocean. The principal component associated with this leading pattern shows a nonsecular increase, with values remaining nearly constant from 1901 to about 1930, then an increase sharply from 1930 to 1944. Then for about 30 years, the values remain near zero. From the mid-1960s to the mid-1980s, the amplitude of the time series increases more rapidly, with a gradual increase after that.

The second REOF is dominated by the variability in the central Pacific associated with the ENSO. Warm SSTs in the tropical central and eastern Pacific are flanked by SST anomalies of opposite sign to the northwest and southwest. There are also weak positive anomalies in the Indian and Atlantic Oceans that are generally associated with a remote oceanic response to the SST variability in the Pacific (Alexander et al. 2002). The associated time series is dominated by variability on the interannual time scale, and it has a correlation of 0.87 with annual mean Niño-3.4 anomalies, but there is evidence of variability on a slower time scale with a period of lower values from the 1950s into the 1970s and a run of higher values in the late twentieth century that is beyond ENSO variability. Moreover, this Pacific pattern has a lag-1 autocorrelation of 0.38, while annual mean Niño-3 values have an autocorrelation of 0.10.

The third REOF has most of its loading in the North Atlantic Ocean and explains 28.9% of variability in the tropical North Atlantic basin alone. The spatial pattern resembles the AMO (Enfield et al. 2001). The time series has large swings and a distinct low frequency behavior. The period from 1901 to about 1930 is predominately associated with a negative phase, followed by a dominantly positive phase from the 1930s to 1970. The phase of the pattern shifts back to negative from 1970 to 1994, before reverting to a positive phase after 1995.

3. Data and models

The six modeling groups that participated in coordinated model simulations as part of the DWG are the National Aeronautics and Space Administration Goddard Space Flight Center (NASA GSFC), the Lamont-Doherty Earth Observatory (LDEO), the Geophysical Fluid Dynamics Laboratory (GFDL), the University of Maryland–National Center for Atmospheric Research...
(UMD–NCAR), the University of Miami–Center for Ocean–Land–Atmosphere Studies (UM–COLA), and the National Centers for Environmental Prediction/Climate Prediction Center (NCEP/CPC). Five of the groups (with the exception of UM–COLA) preformed the experiments with a global AGCM forced with the identical SSTs. UM–COLA preformed the experiments with a coupled model. The atmospheric models employed in the experiments were the NASA Seasonal-to-Interannual Prediction Program (NSIPP1) AGCM (Bacmeister et al. 2000; Schubert et al. 2004a), the NCAR Community Climate Model (CCM3) (Kiehl et al. 1998; Seager et al. 2005), version 2.1 of the GFDL Atmospheric Model (AM2.1) (Delworth et al. 2006; The GFDL Global Atmospheric Model Development Team 2004; Milly and Shmakin 2002), version 3.5 of the NCAR Community Atmosphere Model (CAM3.5), and the NCEP Global Forecast System (GFS) (Campana and Caplan 2009). These five models have diverse developmental histories and comprise both spectral and grid-point models, different physical parameterizations, and different spatial resolutions. More details about the individual models can be obtained in the references included above or in Schubert et al. (2009).

In addition to the HADISSTv1 SST data, other observational datasets include the gridded observed precipitation from the Global Historical Climate Network (GHCN) on a 5° × 5° grid (Vose et al. 1992) and surface temperature observations from version 3 the Hadley

![Reconstructed EOFs](image-url)  
**Fig. 1.** The three leading rotated EOFs of the HADISST annual mean SST for 1901–2004. Combined, these three EOFs explain over 53% of the interannual variance. The contour interval for the left panels is 0.1 K with the zero contour omitted.
Centre–Climate Research Unit’s monthly temperature dataset (HadCRUT3) (Brohan et al. 2006) that incorporates both land and sea surface temperature observations onto a $5^\circ \times 5^\circ$ grid.

4. AGCM experiments

The five modeling centers executed a series of idealized AGCM simulations, and four of them also provided long simulations forced with observed SSTs over the twentieth century. The periods simulated are listed in Table 1 for the model data available. Not every group included all of the experiments, but did every group produce an ensemble of AMIP-type long simulations to quantify climate variability over the entire twentieth century. Specific AGCM simulations are described next.

a. AGCM simulations with idealized SSTs

The purpose of the idealized experiments was to isolate the atmospheric and terrestrial influence of each SST pattern separately, as it is difficult to do so either in the AMIP simulations or in the observations. To assess the relative role of each SST pattern, a series of AGCM simulations forced with the spatial pattern of SST to quantify climate variability over the entire twentieth century. Specific AGCM simulations are described next.

<table>
<thead>
<tr>
<th>Model</th>
<th>Number of ensemble members</th>
<th>Simulated years</th>
</tr>
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<tbody>
<tr>
<td>NASA/NSIPP</td>
<td>14</td>
<td>1902–2004</td>
</tr>
<tr>
<td>LDEO/CCM3</td>
<td>16</td>
<td>1856–2006</td>
</tr>
<tr>
<td>GFDL/AM2.1</td>
<td>10</td>
<td>1870–1999</td>
</tr>
<tr>
<td>NCAR/CCM3.5</td>
<td>1</td>
<td>1901–2004</td>
</tr>
</tbody>
</table>

Each modeling center ran several long simulations with the idealized SST patterns, as well as a control run with the climatological SSTs. The runs varied between 36 years for NCEP GFS and 51 years for the other models with the first year discarded as startup. Both positive and negative polarity of each pattern was used to force the AGCM simulations. In addition, various combinations of patterns were also used in additional experiments. In total, there were 15 different experiments run with specified SST patterns. The results presented in this paper are for the model response to each of the individual SST patterns, and do not address how the atmospheric response to the SST patterns interplay with each other, or the relative role of the tropical versus extratropical SSTs.

b. AMIP simulations

Several of the modeling groups also ran an ensemble of long AMIP simulations forced with observed SST: NSIPP included 14 members, GFDL 10 members, CCM3 16 members, and CAM3.5 1 member. The ensembles of simulations were generated by perturbing the atmospheric initial conditions at the initial time of the integration and allowing the model atmospheric and land state to evolve freely over the observed monthly SST data.

A multimodel mean (MMM) from all of the AMIP simulations was created for the analysis. MMM was produced by removing 1) the model’s respective climatology for the years 1902–99 (common years among all AMIP simulations used) and 2) averaging all 41 members together to create a multimodel ensemble mean. Averaging across such a large ensemble, and across four AGCMs, greatly minimizes the internal noise in the atmospheric variability. Further, averaging across the four models also decreases the impact of model biases, although the procedure is not perfect since the size of the ensemble is not uniform across the models.

5. Results

a. Observed relationship

We first analyze the observed temperature and precipitation to see if there is a relationship between these meteorological variables and three modes of the SSTs. Composites based on plus/minus one standard deviation of the three leading principal components were created to quantify the observed relationship (Fig. 2). The years making up each composite are listed in Table 2.

For the composites associated with the trend mode (Fig. 2, top panels) it is apparent that there is a positive precipitation trend over the eastern part of the United States and Australia. In addition, most of the land areas with data coverage show an increase in temperature. An exception is a tendency toward cooler temperatures in
the southeast United States. The trends over the United States are similar to ones reported by Robinson et al. (2002), Kunkel et al. (2006), and Wang et al. (2009), among others.

The composites of the Pacific SST pattern (Fig. 2, middle panels) show an increase in precipitation over the central and southern United States and decreased precipitation covering most of Australia. The temperature composite shows warming over the northern and western portions of the United States and cooler temperatures over the southern tier states. There are also below average temperatures covering eastern Europe.

The composites of the Atlantic pattern (Fig. 2, bottom panels) show signs of decreased precipitation over parts of the United States, Hawaii, and northern Australia and an increase over Europe. The temperature composite shows warmer than average temperatures for most of North America.

b. Relationship in AGCM simulations

The observed temperature and precipitation composites are next compared with the composites based on the multimodel mean of AMIP simulations. Composites based on the principal components of the three leading SST REOFs are computed in the same way as for the observations. Since the AGCMs do not have the spatial sampling problems that observations have, the AGCM-based composites provide a coherent spatial structure of how the atmosphere responds to various SST patterns. Further, as the AMIP composites are based on averaging over a 30-member ensemble—a process that minimizes the influence of the atmospheric internal
variability—the statistical significance of the composite is also high. The 30 members were equally taken from the CCM3, GFDL, and NASA runs to avoid biasing the results toward one model.

The composites based on the AMIP simulations are shown in Fig. 3. The precipitation response to the SST trend pattern (Fig. 3, top panels) is mostly limited to the tropical oceans, but the temperature composites show broad areas of warmer temperatures. In contrast to a same sign trend in SSTs, except in the eastern Pacific, the precipitation response has both positive and negative rainfall anomalies. This is consistent with mass continuity across pressure surfaces such that increased precipitation, and an associated increase in vertical motion, has to be balanced by increased downward motion and decreased precipitation (Kumar et al. 2004; Chou et al. 2006). On the other hand, the temperature and 200-mb response show a positive anomaly almost everywhere, similar to the documented influence of warmer SSTs (Hoerling et al. 2008; Compo and Sardeshmukh 2008).

The response to the Pacific SSTs (Fig. 3, middle panel) is similar to the observations, with an increase in precipitation over central North America and South America, and a decrease over the Maritime Continent and Australia. Since the models are globally complete, a response over the open ocean can also be inferred. Increased precipitation is found near the date line and is surrounded by a horseshoe pattern of negative precipitation anomalies. The temperature response is also similar to observations—with warm temperatures over western Canada, cooler temperatures over the southern United States, and a warming over tropical land areas—and is similar to the known ENSO impact (Peng et al. 2000).

The precipitation response to the changes of tropical Atlantic SSTs (Fig. 3, bottom panels) shows an increase where the SSTs are also positive, and into the Gulf of Mexico, with a decrease in precipitation extending northward into the contiguous United States. There is also a decrease in precipitation that extends across nearly the entire Pacific basin. The temperature response to this SST forcing causes warmer than average temperature for central North America and for much of Eurasia.

c. Atmospheric response in the AGCM simulations with idealized SSTs

A potential caveat with the composite analysis based on the observed data and the AMIP simulations is that the SST modes never occur in isolation and, hence, the corresponding atmospheric response could have contributions from other SST anomalies. This shortcoming is rectified based on the analysis of AMIP simulations forced with idealized AGCM simulations in which the SST forcing is specified for one mode at a time.

The atmospheric response in the idealized experiments is defined as the multimodel mean of the positive polarity minus the negative polarity experiments for each SST mode. The annual mean response in temperature, precipitation, and 200-mb height for the three leading SST patterns is shown in Fig. 4. Apart from the composite based on the multimodel mean, agreement between model responses for different SST forcing patterns is also assessed. To quantify the agreement in the sign of the ensemble mean response, regions shaded in Fig. 4 are where at least four out of the five models agree (three out of four for the trend, as CCM3.5 did not complete AGCM simulations with the negative trend of SSTs) on the sign of the response.

The precipitation response to the trend in SST pattern is mainly confined over the ocean and coastal regions. The response includes an increase in precipitation over the southern tip of India, extending eastward across the Maritime Continent, with a decrease in precipitation over the central equatorial Pacific. There is also an increase in

<table>
<thead>
<tr>
<th>Trend</th>
<th>Pacific</th>
<th>Atlantic</th>
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<tr>
<td>Warm</td>
<td>1902, 1905, 1919, 1926, 1930,</td>
<td>1915, 1926, 1931, 1937, 1938,</td>
</tr>
<tr>
<td>Cool</td>
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<td>1903, 1904, 1912, 1913, 1914,</td>
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<td></td>
<td>1927, 1928, 1929, 1930, 1931,</td>
<td>1994</td>
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<td>1932</td>
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precipitation over Central America. The temperature response is for a warming over most of the globe. We also note that the spatial pattern of the response to the trend SST pattern in the idealized simulations matches quite well the composite response inferred based on the AMIP simulations. The 200-mb height response to the trend shows a large-scale increase in height in the tropics and midlatitudes. The increase in height is maximized just south of the Aleutian Islands and southern parts of the Pacific Ocean.

The Pacific SST pattern (Fig. 4, middle panels) has a more robust response, with increased precipitation over most of the equatorial Pacific and a decrease over the Maritime Continent. There is also a decrease in precipitation over the Amazon, extending across the tropical Atlantic Ocean into Africa, and an increase in precipitation over North America and the southern portion of South America. The temperature response shows warming over the tropical landmasses and over northwestern Canada into Alaska and a cooling over the central United States. The height response shows symmetry across both Northern and Southern Hemispheres with the largest height departures east of the date line just off of the equator and a negative height poleward and west of the maximum positive response. In general, the spatial pattern for the precipitation and temperature composites matches remarkably well the one inferred from the AMIP simulations with the observed evolution of SSTs.

The precipitation response to the North Atlantic SST pattern shows an increase over the regions of positive SST anomalies and reduced precipitation for most of the globe, with the exception of the Indonesian region. The surface temperature response is a large-scale warming that extends across northern Africa and into southern Asia. The response pattern is similar to the AMIP run in regions where the idealized response agrees among the models. There is also a signal of increased surface temperature response over the southern Great Plains, and Mexico, as well as central South America, which is also consistent with the AMIP composite. The 200-mb height response shows an increase in heights over the tropical Atlantic sector and a decrease in heights in the higher
latitudes of both hemispheres, but having a larger zonal extent in the Southern Hemisphere. There is also an increase in height around the date line in the North Pacific but lower heights over the Yukon, which suggests a wave train emanating from the tropical western Pacific. This circulation anomaly is more pronounced in boreal winter (not shown) when the precipitation along the South Pacific convergence zone (SPCZ) is suppressed and precipitation in the eastern Indian Ocean enhanced. These results are similar to what has been found in previous works (Schubert et al. 2004b; Sutton and Hodson 2005; Seager 2007).

d. Analysis of change in the probability distribution function of precipitation

It is well known that, for a given SST forcing, the time-averaged atmospheric state is not unique and has to be characterized by a probability density function (PDF) (Kumar and Hoerling 2000). The analysis of the composites only provides inference about the mean atmospheric response to changes in SSTs. It is possible that, even though the influence of SSTs on the mean of the PDF may be small (as is the case for the precipitation response for the trend and the Atlantic SST pattern), changes in the extremes of the PDF may still be appreciable. To assess this possibility, the PDF of annual mean precipitation anomalies for the Great Plains for the three SST modes is analyzed (Fig. 5) from the idealized experiments. The Great Plains region (30°N–30°S, 95°–105°W) is chosen because of observational evidence for long-term droughts (Seager et al. 2005). The PDFs of annual mean precipitation are constructed for the positive and negative phases of SST anomalies separately.
The greatest separation in the PDFs of the annual mean precipitation over the Great Plains is for the Pacific SST mode, followed by a weaker influence for the Atlantic SST mode. The influence of the trend SST mode is small and also does not indicate any evidence of changes in the extremes for the annual mean precipitation.

One goal of the DWG was to understand the relationship between the long-term droughts and SST variability in different ocean basins. Assuming that precipitation deficits are also related to drought indices, we quantify the odds for below normal precipitation anomalies for several years in a row. For this purpose, simulations from all of the models are pooled together, and the annual mean precipitation resampled to calculate the odds of having below normal precipitation anomalies three consecutive years. The samples of annual-mean precipitation are drawn with replacements, and the odds are calculated by counting how many times the sample contained all three years of negative precipitation anomalies. The resampling was done 1 000 000 times for each SST pattern. If the annual mean precipitation is a random variable with a normal distribution, the expected probability for three consecutive years of below normal precipitation is 12.5%. A drawn sample having all three years containing a negative precipitation anomaly is counted as falling into the 3-dry-yr category; if any of the three years had a positive anomaly, then it does not count as having three dry years in this estimate.

The Monte Carlo estimate for the warm Pacific SST pattern shows only a 0.1% chance of having three consecutive years of below average precipitation, compared to 78.9% when the Pacific is cool. The Atlantic SST pattern forces a shift in probability from a 36.5% chance of having three dry years in the warm phase versus a 3.5% chance when it is cool. The trend SST pattern shifts the chance to 24.0% for the warm pattern compared to 6.7% when the SSTs were cool. The climatology runs for all models pooled together give a 13.0% chance of having three dry years. The deviation from 12.5% is due to the skewness of precipitation. The complete results, including analysis for precipitation averaged over other geographical regions, are shown in Table 3. These estimates show that long-term multiyear rainfall deficits (and long-term droughts) are most likely to occur when the Pacific Ocean is cool or the Atlantic Ocean is warm. The analysis also shows that the likelihood of having a long-term drought increased in response to the linear trend SST pattern. We should point out that a precipitation deficit as a proxy for droughts does not include the influence of increases in temperature, which by increasing evapotranspiration can also lead to hydrological stress and could be a major contributor to water balance (Easterling et al. 2007).

e. Reconstruction of precipitation variability in the AMIP simulation

In the final analysis, the inferred atmospheric and terrestrial responses related to the three modes of SST are used to reconstruct the climate variability for the twentieth century. Recall that, to increase the signal-to-noise ratio and make the identification of the atmospheric response easier for the idealized experiments, the amplitudes of the modes of SST variability were multiplied by a constant factor. Assuming that the response to each SST pattern is linear, the reconstruction is based on summing up the idealized responses for the annual means to the three SST modes [with the response to each pattern scaled by the normalized principal component (PC) value for that year]. The reconstructed response for 1900–2004 is compared with the SST response.
in the AMIP simulations to assess the role of three discrete modes of SSTs.

The temporal coherence between the reconstructed and AMIP-simulated response for precipitation, surface temperature, and 200-mb heights is assessed based on the anomaly correlation. The spatial pattern of temporal correlation for each grid point is shown in Fig. 6. Over the oceans, the correlations for temperature are highest where the loading patterns of the REOFs are also highest. The correlation is also high over most of the continental landmasses, particularly in tropical latitudes. The precipitation correlations are smaller away from the direct influence of the SST variability. Two regions of largest correlation over continental regions are the central United States and an area extending eastward from the Black Sea in Europe. Finally, most of the SST-forced variability for the AMIP-simulated 200-mb heights is associated with the three leading SST modes. We should point out that this analysis is for reconstructing the SST ensemble mean response based on the sum of the response due to the leading modes of SSTs and does not include contribution from atmospheric internal variability.

To focus on the precipitation variability over the Great Plains region alone, time series of annual precipitation from the AMIP simulations and the reconstruction based on the idealized experiments is shown in Fig. 7. The correlation between the AMIP mean and reconstruction is 0.9. Analysis of the contribution from each mode indicates that the largest contribution is because of the Pacific SST mode (not shown). One of the largest differences, spanning several years, between the two time series occurs during the Dust Bowl period of the 1930s. While the AMIP runs show dry conditions during this time, the analysis based on the reconstruction, on average, shows weaker negative anomalies. Also shown in Fig. 7 are the observed precipitation anomalies. The general character of the interannual variability of the observations is captured by the AMIP mean. The main difference is that the AMIP mean has less variability, which is expected from an ensemble mean.

The reconstruction approach can also be used to assess the influence of different SST analyses on the inferred precipitation response over the United States. To the extent that the atmospheric response based on the idealized AGCM simulations is additive and can be scaled according to the amplitude of the respective SST modes (as is evident from the high correlation between the two time series in Fig. 7), this is a viable approach without redoing the AMIP simulations with an alternate SST analyses.

One alternate SST analysis that we consider uses version 3b of the Extended Reconstructed SST (ERSSTv3b) dataset, which is similar to ERSSTv3, but withholds all of the satellite data to provide a more uniform SST record (Smith et al. 2008; Xue et al. 2003). The ERSSTv3b and HADISST SST anomalies for the Dust Bowl period are shown in the left panels of Fig. 8. The SST composite for 1932–38 from the HADISST (Fig. 8a) data shows a weak cool anomaly extending from the central equatorial Pacific Ocean eastward and northward to the California coast and the North Pacific Ocean is also cool between 30° and 40°N. In contrast, the ERSSv3b (Fig. 8c)
data shows a substantial cool SST anomaly near the date line and equator with the largest negative anomaly less than $-0.6^\circ$C and for the SSTs across the North Pacific Ocean the SST anomalies are warmer than for the HADISST dataset. To put these different SST estimates into the context of the model simulations already performed, both HADISST and ERSST are projected onto the leading REOFs of the HADISST. These projections are shown on the right-hand side of the Fig. 8. The HADISST data produces a weak projection on these three EOFs (Fig. 8b), with the trend pattern dominating (refer to Fig. 1). The projection of the ERSST data shows a much stronger projection onto the Pacific pattern and also a warmer Atlantic Ocean (Fig. 8d).

As the projection of two SST datasets on the three leading REOFs is appreciably different, we also assess the influence of differences in SSTs for the climate over the United States based on the reconstruction. The surface temperature and precipitation anomalies averaged over the Dust Bowl period are compared in Fig. 9. As indicated by the time series in Fig. 7, the reconstructed precipitation anomalies based on the HADISST data are weaker than the corresponding AMIP simulations. Consistent with the weaker precipitation, surface reconstructed temperature anomalies are also weaker than for the AMIP. Further, both surface temperature and precipitation anomalies are also weaker than for the observations and are shifted southeastward. Because of the stronger amplitude of the projection of the ERSSTv3 on the three leading SST REOFs, the reconstructed surface temperature and precipitation response over the United States is stronger. Since the spatial structure of the reconstructed anomalies is constrained to be invariant, the differences are highlighted by differences in the amplitudes of the reconstructed anomalies. This simple analysis highlights the importance of the differences in the SST analysis on the understanding, and attribution, of climate variability in the twentieth century, particularly for the earlier period when large errors in the SST analysis due to data scarcity exist.

6. Conclusions

In this paper, the influence of the leading modes of SST variability on the terrestrial climate, with a particular focus over the United States, was studied. The analysis approach included identification of the leading modes of SST variability and a coordinated set of AGCM simulations forced with the SST modes. Inclusion of the multiple AGCMs is necessary to enhance confidence in the reliability of the results.

Based on their spatial structure and the corresponding principal component time series, the three leading modes of SSTs included a trend mode and a Pacific and
an Atlantic mode. Consistent with previous studies, and the well-documented global influence of SST variability in the tropical Pacific, the atmospheric influence of the Pacific mode was the largest. The Atlantic pattern also shows a significant role in driving the global climate but to a lesser extent than that of the Pacific Ocean. Beyond the local influence of SST anomalies, a global response is achieved by an increase in precipitation over the warmer Atlantic SSTs that leads to a reduction of precipitation over the tropical Pacific warm pool, and this reduction produces a wave train across the North Pacific into North America. In the extratropics, and for the precipitation, the continental region of the United States is one of the most sensitive regions to variations in SST. This conclusion was unanimously based on the analysis of the observed data, as well as AMIP and idealized AGCM simulations (Figs. 2–4). Our analysis also included changes in the PDF for the annual mean precipitation over the Great Plains region. The results indicate that the probability of precipitation deficit is largest for the cold phase of the Pacific SST mode, with the positive phase of the Atlantic SST mode also playing a role.

The reconstruction of the annual mean variability based on the response obtained from the idealized experiments had a close resemblance with the response in the AMIP simulations in which observed variations in the global SSTs are specified. This analysis attests to the fact that the SST modes identified herein, and their atmospheric influence, make a dominant contribution to the atmospheric response inferred in the AMIP simulations forced with observed global SSTs. This is further confirmed based on the comparison of time series of the precipitation over the Great Plains (Fig. 7).

Based on the reconstruction approach, we also assess the role of differences in the SST analysis, particularly their influence on the precipitation averaged over the Dust Bowl period. A surprising conclusion from this analysis is that, for the SST reconstructed based on the HADISST, the modes were unable to capture the drying in the AMIP simulation. One possible explanation is that for the Dust Bowl period the projection of HADISST on the modes of SST identified herein was small. Although the reconstruction based on the ERSST does produce a stronger negative precipitation anomaly, it is still weaker than the observations and is displaced too far to the south. One possibility for the lack of agreement with observations is the lack of aerosols in these models, which have been shown to play an important role during this period (Cook et al. 2008).

To the extent that the precipitation variability could be associated with the occurrence of droughts, the results from the multimodel AGCM simulations have implications for drought variability and predictability, particularly over the United States. Consistent with earlier
FIG. 9. (left) Precipitation and (right) surface temperature anomalies averaged for the period 1932–38. The top row is from the AMIP multimodel mean. The middle row is taken from projecting the ERSSTv3b SST data onto the 20 leading REOFs of HADISST, and reconstructing the temperature and precipitation anomalies from the linear response to these patterns. The third row is same as the second, expect for projection of the HADISST data. The fourth row is the observed composites.
studies (Hoerling and Kumar 2003; Schubert et al. 2004a), the likelihood of droughts over the central United States is greatly enhanced during the cold phase of the Pacific SST mode, with the potential for an additional contribution from the positive phase from the Atlantic SST mode. Furthermore, possible local feedbacks leading to warmer surface temperatures can exacerbate the influence of the precipitation deficit on soil moisture and drought. Although the SST trend mode does not have an appreciable influence on precipitation over the central United States, the associated warmer surface temperature, and its influence on the surface evaporation, can also exacerbate the possibility of droughts.

The importance of the SST modes in controlling precipitation and drought variability also has relevance for ongoing efforts in initializing decadal predictions as part of the IPCC CMIP5 experimental design (Meehl et al. 2009). Since prediction of the SST modes discussed in this paper is ultimately a coupled ocean–atmosphere problem, it will be imperative to monitor and assess the predictability of SST modes in the decadal prediction efforts. The analysis presented here lays the framework for understanding the remote influence of the modes of SST variability on the terrestrial climate, and documents the potential predictability associated with known structures of SST variability: to what extent the predictability can be realized can next be examined based on the coordinated set of initialized decadal prediction runs.

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REFERENCES


