

Imprint of the Atlantic multi-decadal oscillation and Pacific decadal oscillation on southwestern US climate: past, present, and future

**Petr Chylek, Manvendra K. Dubey,
Glen Lesins, Jiangnan Li & Nicolas
Hengartner**

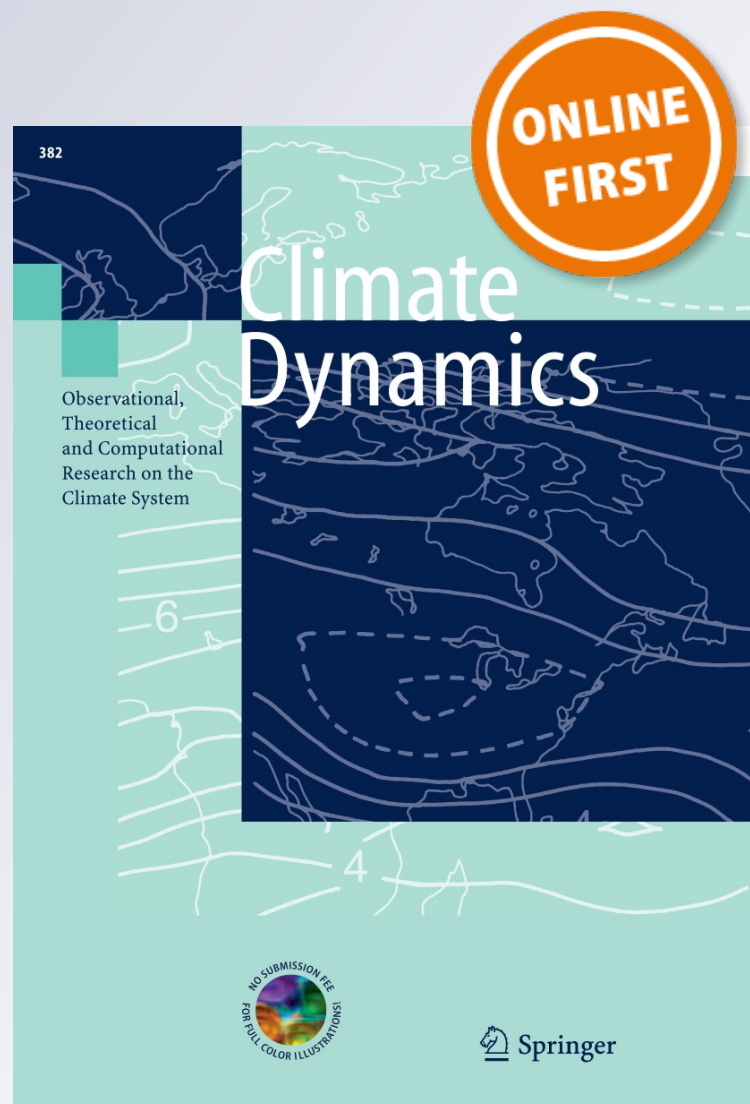
Climate Dynamics

Observational, Theoretical and
Computational Research on the Climate
System

ISSN 0930-7575

Clim Dyn

DOI 10.1007/s00382-013-1933-3



Your article is published under the Creative Commons Attribution license which allows users to read, copy, distribute and make derivative works, as long as the author of the original work is cited. You may self-archive this article on your own website, an institutional repository or funder's repository and make it publicly available immediately.

Imprint of the Atlantic multi-decadal oscillation and Pacific decadal oscillation on southwestern US climate: past, present, and future

Petr Chylek · Manvendra K. Dubey ·
Glen Lesins · Jiangnan Li · Nicolas Hengartner

Received: 21 February 2013 / Accepted: 26 August 2013
© The Author(s) 2013. This article is published with open access at Springerlink.com

Abstract The surface air temperature increase in the southwestern United States was much larger during the last few decades than the increase in the global mean. While the global temperature increased by about 0.5 °C from 1975 to 2000, the southwestern US temperature increased by about 2 °C. If such an enhanced warming persisted for the next few decades, the southwestern US would suffer devastating consequences. To identify major drivers of southwestern climate change we perform a multiple-linear regression of the past 100 years of the southwestern US temperature and precipitation. We find that in the early twentieth century the warming was dominated by a positive phase of the Atlantic multi-decadal oscillation (AMO) with minor contributions from increasing solar irradiance and concentration of greenhouse gases. The late twentieth century warming was about equally influenced by increasing concentration of atmospheric greenhouse gases (GHGs) and a positive phase

of the AMO. The current southwestern US drought is associated with a near maximum AMO index occurring nearly simultaneously with a minimum in the Pacific decadal oscillation (PDO) index. A similar situation occurred in mid-1950s when precipitation reached its minimum within the instrumental records. If future atmospheric concentrations of GHGs increase according to the IPCC scenarios (Solomon et al. in *Climate change 2007: working group I. The Physical Science Basis*, Cambridge, 996 pp, 2007), climate models project a fast rate of southwestern warming accompanied by devastating droughts (Seager et al. in *Science* 316:1181–1184, 2007; Williams et al. in *Nat Clim Chang*, 2012). However, the current climate models have not been able to predict the behavior of the AMO and PDO indices. The regression model does support the climate models (CMIP3 and CMIP5 AOGCMs) projections of a much warmer and drier southwestern US only if the AMO changes its 1,000 years cyclic behavior and instead continues to rise close to its 1975–2000 rate. If the AMO continues its quasi-cyclic behavior the US SW temperature should remain stable and the precipitation should significantly increase during the next few decades.

P. Chylek (✉)
Space and Remote Sensing, Los Alamos National Laboratory,
Los Alamos, NM, USA
e-mail: chylek@lanl.gov

M. K. Dubey
Earth and Environmental Sciences, Los Alamos National
Laboratory, Los Alamos, NM, USA

G. Lesins
Department of Physics and Atmospheric Science, Dalhousie
University, Halifax, NS, Canada

J. Li
Canadian Centre for Climate Modeling and Analysis,
Environment Canada, Victoria, BC, Canada

N. Hengartner
Theoretical Biology and Biophysics, Los Alamos National
Laboratory, Los Alamos, NM, USA

1 Introduction

Climate change in the southwestern US is of concern because a slight increase in temperature and decrease in precipitation can transform the semi-arid land into a desert-like landscape (Seager et al. 2007; MacDonald 2010; Cayan et al. 2010; Williams et al. 2012). The region has experienced several severe droughts in the recent and distant past (Woodhouse et al. 2010; Cook et al. 2010; Touchan et al. 2011; Fawcett et al. 2011; Oglesby et al. 2012). Current climate models forecast an

imminent transition to a more arid climate (e.g. Seager et al. 2007; Williams et al. 2012).

The global climate change is driven by increasing atmospheric concentration of greenhouse gases (GHGs) as well as by natural climate variability (Wu et al. 2007, 2011a; Tung and Zhou 2013). While the warming by increasing GHGs is well captured by climate models (Solomon et al. 2007), the treatment of natural variability remains a challenge (Dai et al. 2005; Zhang et al. 2007; Solomon et al. 2011; Wyatt et al. 2011).

The AMO index which tracks the North Atlantic sea surface temperature (SST) variability may be tied to the Atlantic meridional overturning circulation (AMOC) (e.g. Knight et al. 2005; Mahajan et al. 2011; Yang et al. 2013). Compo and Sardeshmukh (2009) found that the recent worldwide land warming has a significant component originating from warmer oceans rather than being a direct effect of increasing greenhouse gases. Semenov et al. (2010) estimated the AMO contribution to post 1970 global warming to be 0.24 °C. Tung and Zhou (2013) found that neglecting the AMO leads to an overestimation of the global mean anthropogenic warming trend during the second half of the twentieth century by about a factor of two. Hansen et al. (http://www.columbia.edu/~jeh1/mailings/2013/20130115_Temperature2012.pdf) suggested that natural variability is responsible for over a decade of stable global mean temperatures since about 2000. On a regional scale the AMO may account for even a larger fraction of temperature variability (Polyakov and Johnson 2000; Chylek et al. 2009, 2010; Mahajan et al. 2011; Humlum et al. 2011).

State-of-the-art coupled atmosphere–ocean general circulation models (AOGCMs) are limited by an incomplete understanding of the related physics as well as by the capacity of even the fastest computers. The extreme complexity of the nonlinear climate system prevents AOGCMs from providing an unambiguous causal description of climate. Research establishing a meaningful decadal climate forecast by properly initiated dynamical models is only beginning (Yang et al. 2013). In this situation, simplified semi-empirical and statistical models (e.g. North 1975; Lean and Rind 2008; Humlum et al. 2011) can provide valuable insights that may complement the mechanistic understanding obtained by AOGCMs simulations.

2 Data

In the following we perform multiple linear regression analysis (Wilks 2006; Lean and Rind 2008; Zhou and Tung 2013) of the southwestern US surface air temperature and precipitation records using historical radiative forcing and natural variability indices as predictors. For our analysis we

consider the southwestern US as a region between latitudes of 31° and 41°N and longitudes of 102°W and 114°W. This is an area comprising approximately the states of New Mexico, Arizona, Colorado, and Utah. Although there are currently many meteorological stations in the US SW, their temperature and precipitation records start at different dates and contain frequent gaps. In the following we use the data (annual mean temperature and precipitation) provided by the NOAA National Climate Data Center (NCDC) at the website (<http://www.ncdc.noaa.gov/oa/climate/research/cag3/nm.html>).

The US SW annual temperature and precipitation (1895–2012) is shown in Fig. 1. The year 2012 was the warmest and 2003 the third warmest year since beginning of this instrumental record in 1895. The warmest multi-year period (5 year moving averages) was centered on the year 2001. The coldest years occurred between 1912 and 1923. The NOAA NCDC temperature records show that the US SW has warmed from 1895 to 2012 at an average rate of 0.08 °C per decade, with much faster warming during the 1915–1935 (0.46 °C/decade) and 1970–2000 (0.40 °C/decade) periods.

The US SW precipitation was more than two standard deviations below the average only during the 1950s

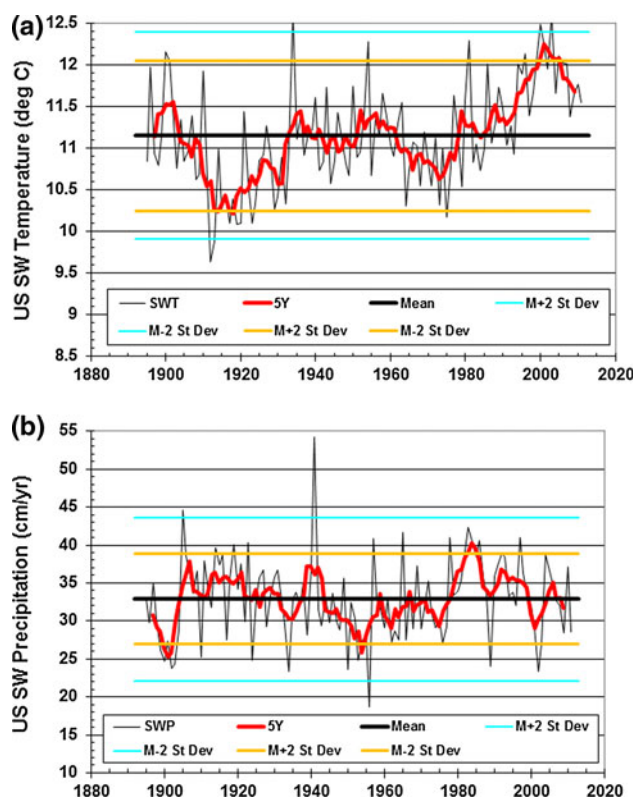


Fig. 1 **a** Southwestern United States (US SW) temperature, **b** precipitation. Annual data (black), 5 year moving average (red), mean (thick black) plus or minus two standard deviations for annual data (light blue) and 5 year moving averages (yellow)

drought (Fig. 1b). The second lowest precipitation occurred in 2002. While the wettest single year was 1941, the highest multiyear precipitation period was 1981–1985. The overall precipitation trend (1895–2012) is slightly positive, however not statistically significant. Thus the US SW has moved towards a warmer climate with a nearly unchanged rate of precipitation during the last 118 years. The post 1985 US SW precipitation decrease is not outside the range of natural variability and in fact a similar decrease occurred between 1940 and 1955.

The temperature and precipitation history of individual states within the US SW (NM, AZ, CO, and UT) resemble closely that of the whole US SW region.

To assemble a set of potential predictors for regression analysis we consider first the forcing used in the Coupled Model Inter-comparison Project phase 5 (CMIP5). These include anthropogenic radiative forcing by increasing

atmospheric concentration of greenhouse gases and aerosols (GHGA), total solar irradiance (SOL), volcanic aerosols (VOLC), and El Nino Southern Oscillation (ENSO).

The twentieth century combined radiative forcing due to increasing anthropogenic greenhouse gases and variable aerosols (GHGA) is taken as prescribed by the CMIP5 RCP Database Version 2.0.5 at website <http://tntcat.iiasa.ac.at:8787/RcpDb/dsd?Action=htmlpage&page=compare>. Variable solar irradiance (SOL) (Foukal 2012) is from Kopp and Lean (2011), and volcanic aerosols (VOLC) from Vernier et al. (2011). To avoid observational uncertainty in the early years of the twentieth century we limit the analysis to 1910–2012. To remove the year to year weather anomalies, we smooth all predictors by calculating first the 5 year moving averages (Fig. 2). To select a set of suitable predictors for the regression analysis we adopt the forward selection procedure to avoid over-fitting and errors in

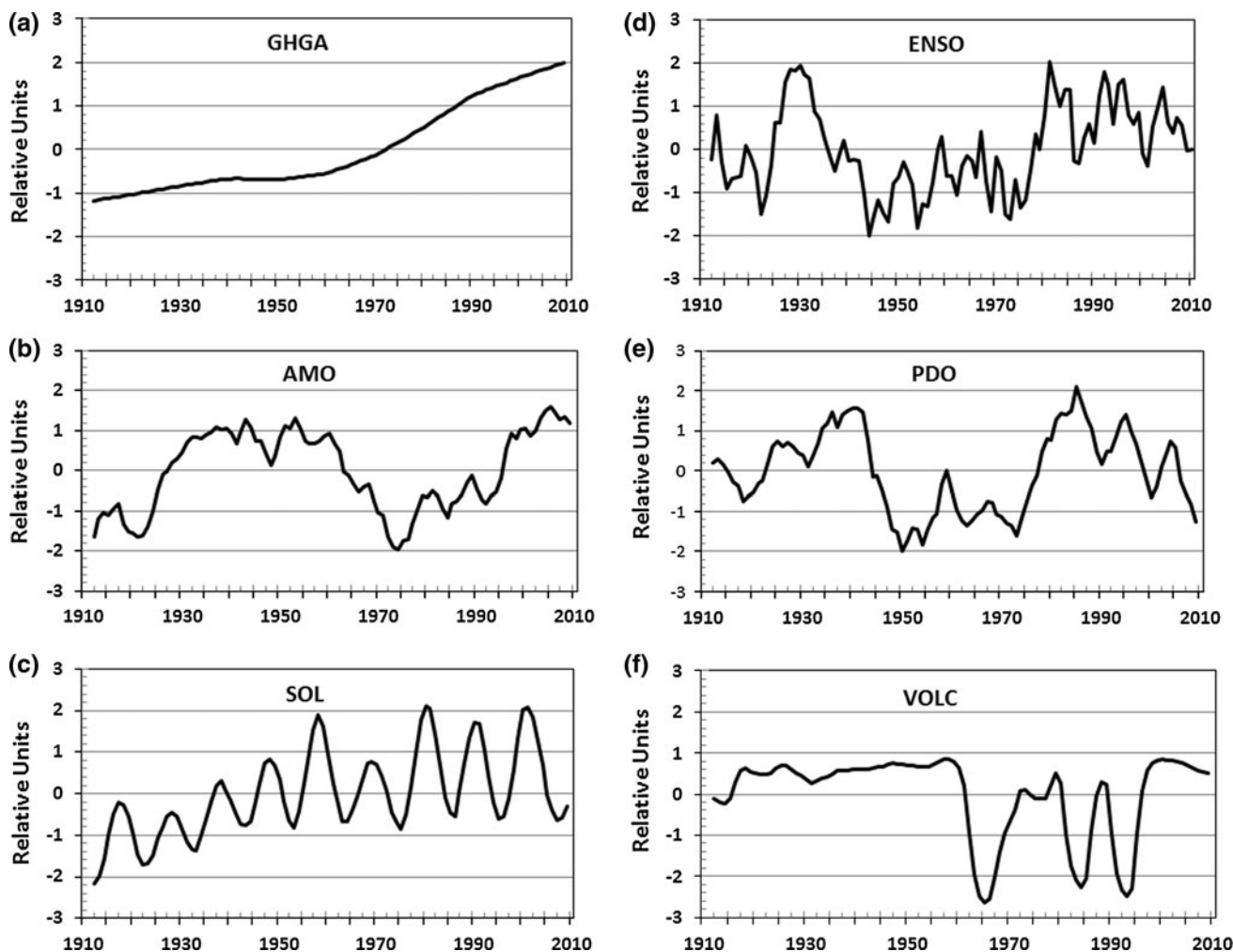


Fig. 2 Explanatory variables (predictors) used in our regression analysis (GHGA—anthropogenic greenhouse gases and aerosols, AMO—Atlantic multi-decadal oscillation, SOL—solar variability, ENSO—El Nino-Southern Oscillation, PDO—Pacific decadal

oscillation, VOLC—volcanic aerosol). All predictors are smoothed by a 5 year moving average, and normalized to zero mean and unit variance

regression coefficients caused by highly correlated predictors (Wilks 2006).

The US SW climate (temperature and precipitation) is highly correlated with oceanic indices. Therefore we add two additional “effective forcings” characterizing the multi-decadal variability of atmosphere/ocean circulation, namely the Pacific decadal oscillation (PDO), and the Atlantic multi-decadal oscillation (AMO). Since current climate models do not reproduce the amplitude and timing of these oscillations in their forced runs, they are generally considered to be an intrinsic property of the climate system that are averaged out in ensemble mean of individual simulations. Although there are several different ways how to characterize the Atlantic Ocean variability (Zanchettin et al. 2013) for our analysis we employ the NOAA unsmoothed AMO long series from <http://www.esrl.noaa.gov/psd/data/timeseries/AMO/>.

3 Regression model of the US SW temperature

The considered predictors are listed in Table 1. Although we start with 102 years of annual temperature data, our 5 year moving averages and the autocorrelation of individual time series reduces significantly the number of independent samples. The effective sample size (Wilks 2006) is reduced to below ten for all the predictors except the ENSO.

None of the predictors by themselves can account for more than 59 % of the observed temperature variance (Table 1). To construct the regression model we consider first the usual forcing used in climate models consisting of GHGA, SOL, VOLC and ENSO. This set of predictors can account for 71 % of the temperature variance (Table 2, line 1). We find that the residual (difference between the observed and regressed temperature) is correlated with the AMO ($r = 0.64$) suggesting that AMO may be a good additional predictor (Fig. 3a). The inclusion of AMO increases significantly the fraction of the US SW

Table 1 List of considered explanatory variables (predictors) for regression analysis of the US SW climate, and their correlation coefficients, r , with the observed US SW temperature and precipitation

Predictor	r (temperature)	r (precipitation)
GHGA	0.77	0.21
SOL	0.52	0.03
VOLC	0.03	−0.32
ENSO	0.31	0.48
AMO	0.65	−0.34
PDO	0.16	0.69

temperature variance accounted for. Just two of the predictors (GHGA and AMO) can account for 86 % of temperature variance (Table 2).

We start the stepwise regression (Wilks 2006) with the GHGA and AMO and add one additional potential predictor. We use the square of the adjusted correlation coefficient (Wilks 2006) R_{adj}^2 , to quantify the goodness of the regression.

For three predictor combinations (Table 2) we find the highest $R_{adj}^2 = 0.87$ for a set of GHGA, AMO, and SOL. Other three predictor sets do not increase the fraction of temperature variance accounted for above that achieved by the GHGA and AMO alone. The addition of the ENSO to this triplet leads to the $R_{adj}^2 = 0.88$. Finally the five predictor set of GHGA, AMO, SOL, ENSO, and PDO reaches $R_{adj}^2 = 0.89$. The relative contribution of the GHGA and AMO is a robust results of our analysis which is independent of the regression model chosen as long as the GHGA and AMO are among the explanatory variables. For further analysis we consider the regression model based on the three predictor set (GHGA, AMO and SOL) as a suitable compromise between complexity and accuracy (with a correlation coefficient $r = 0.94$ and $R_{adj}^2 = 0.87$).

The past US SW temperature (in °C) can be now approximated (using corresponding regression coefficients) by a linear regression

$$T(t) = 11.13 + 0.29GHGA(t) + 0.24AMO(t) + 0.07SOL(t) \quad (1)$$

where each dimensionless predictor is normalized to zero mean and unit variance.

Table 2 Considered regression models of the US SW temperature

n	k	SW Temperature predictors	R_{adj}^2
1	4	GHGA, SOL, VOLC, (ENSO)	0.71
2	2	GHGA, AMO	0.86
3	3	GHGA, AMO, SOL	0.87
4	3	GHGA, AMO, (VOLC)	0.85
5	3	GHGA, AMO, ENSO	0.86
6	3	GHGA, AMO, PDO	0.85
7	4	GHGA, AMO, SOL, ENSO	0.88
8	4	GHGA, AMO, SOL, (VOLC)	0.87
9	4	GHGA, AMO, SOL, (PDO)	0.87
10	5	GHGA, AMO, SOL, ENSO, (VOLC)	0.88
11	5	GHGA, AMO, SOL, ENSO, (PDO)	0.89
12	6	GHGA, AMO, SOL, ENSO, PDO, (VOLC)	0.89

The n is the model number, k is the number of predictors in the given model, and R_{adj}^2 (Wilks 2006) provides the fraction of the observed temperature variance accounted for by the given model. The parenthesis around the acronym of an explanatory variable indicates that the predictor is not statistically significant at $p = 0.05$ significance level

To check how the regression coefficients depend on the uncertainty of the predictors, we have added to each predictor time series (GHGA, AMO, SOL) annual value random numbers (zero mean and standard deviation of 0.1) and repeated the regression reconstruction. The regression coefficients appearing in Eq. (1) changed slightly to: 11.13, 0.31, 0.23, and 0.04. Thus the considered uncertainty of about 10 % in the predictor values does not change significantly the results of our analysis (specifically they do not change the relative contributions of the GHGA and AMO).

To demonstrate that our results do not depend on the exact source of the data, we have also reconstructed the US SW temperature using meteorological stations data. We used all the stations within US SW that are used in the NASA GISS temperature analysis and that have at least 90 % complete annual mean temperature for the years 1920–2012. This temperature set produced a very similar regression results with the ratio of the GHGA to AMO regressions coefficients of 1.23 compared to 1.21 obtained with the NOAA NCDC data.

The regression reconstructed temperature with two (GHGA and AMO) or three (GHGA, AMO, and SOL) predictors, and the observed US SW temperature are shown in Fig. 3b while contributions of individual predictors to

the US SW temperature are shown in Fig. 3c, d. According to our regression analysis the early twentieth century US SW warming (1915–1935) and the following cooling period (1955–1975) were dominated by the AMO with only minor contributions from GHGA and SOL. The contributions to the post 1975 warming trend were about equally divided between the GHGA and AMO (Fig. 3c, d). A variability of solar irradiance (SOL) had only a minor influence on the late twentieth century US SW warming.

A relative apportion of temperature between the AMO and GHGA is a robust result that does not depend on the final selection of predictors as long as the AMO and GHGA are among them. Even when only the AMO and GHGA are used the R_{adj}^2 decreases only to 0.86 (Table 2). We have also analyzed a smaller version of the US SW consisting just of AZ and NM as well as individual states alone. We found identical conclusions with only minor differences in the proportion of the GHGA and AMO in explaining the temperature time series.

4 US SW temperature projection until 2050

Assessment of future climate change in the US SW is needed for planning future developments, water

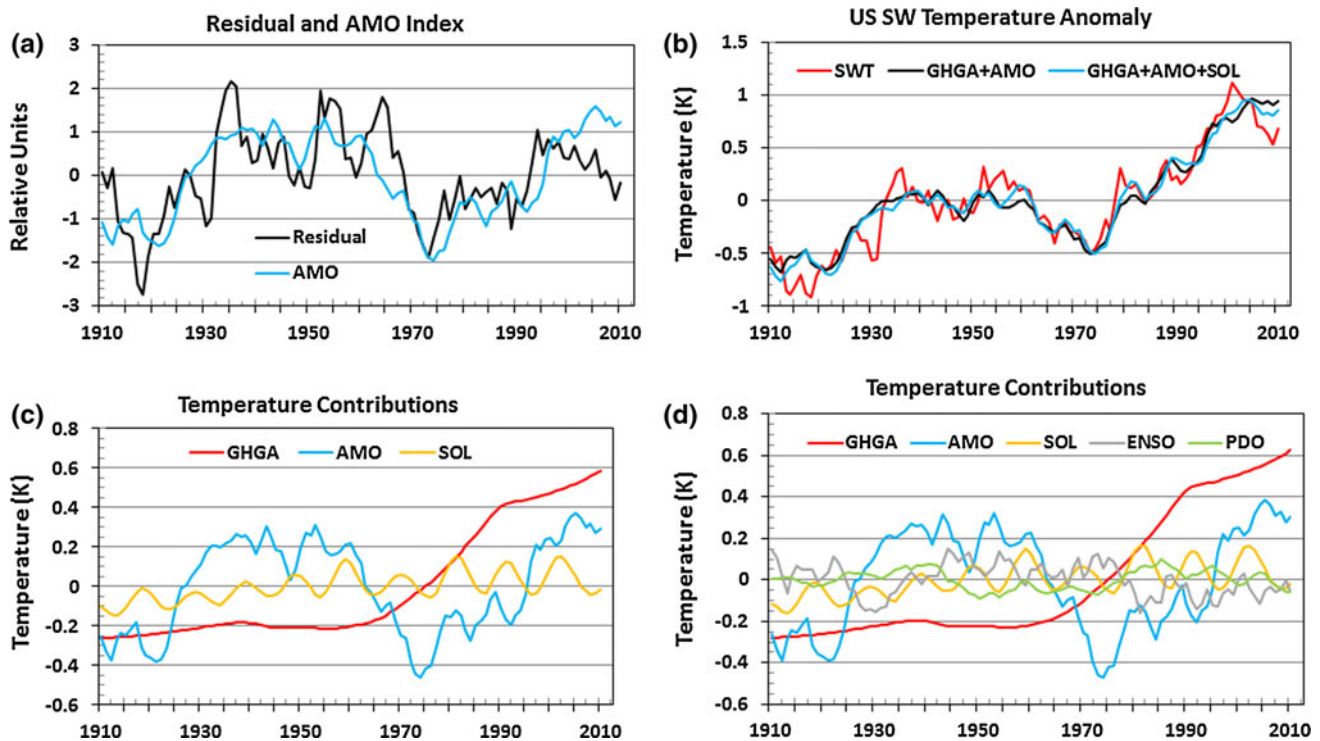


Fig. 3 **a** Residual of the regression model with the known radiative forcing and ENSO as predictors (black) and the AMO index (blue). **b** US SW observed temperature (red) and its regression reconstruction using GHGA and AMO as predictors (black) or GHGA, AMO, and SOL (blue). **c** Individual contributions to the US SW temperature

variability due to anthropogenic greenhouse gases and aerosol (GHGA), Atlantic multi-decadal oscillation (AMO), and solar variability (SOL). **d** Same as **c**, however, with GHGA, AMO, SOL, ENSO and PDO as a set of explanatory variables

availability, and forest management. Currently the climate models (CMIP3 and CMIP5 simulations) serve as basic tools for this task. Although climate models are quite successful in reproducing the past global and continental scale temperature variability, their application to regional climate is less reliable (Kerr 2013; van Oldenborgh et al. 2013). The same reservation applies to nested regional climate models or dynamical downscaling by regional models that are forced by boundary conditions produced by AOGCMs simulations.

To supplement projections provided by the coupled atmosphere–ocean climate models we use the above regression reconstruction of the US SW temperature to assess possible changes for the next few decades. To estimate the future temperature changes using the above regression equation we need the future projection of the AMO, SOL, and GHGA forcing. For the GHGA we use the CMIP5 prescribed path RCP4.5 leading to 487 ppm of CO₂ by the year 2050. Although some other studies use the RCP8.5 to demonstrate maximum warming and the most devastating consequences, we consider the RCP4.5 scenario to be the closest what we can expect with an average CO₂ concentration increase of about 2 ppm/year. The future solar variability is not expected to be substantially different from the variability observed within the last four to five solar cycles, thus a repetition of the past four cycles is a reasonable assumption.

Predicting the future behavior of the AMO is more problematic. Although there have been several attempts to deduce the past AMO behavior (Latif et al. 2004; Delworth and Mann 2000; Keenlyside et al. 2008; Ting et al. 2009; Chylek et al. 2011, 2012; Knudsen et al. 2011) its future evolution is uncertain. Booth et al. (2012) based on the HadGEM2-ES earth system model simulation suggested that the twentieth century observed Atlantic variability was caused by anthropogenic aerosols. However, Zhang et al. (2013) showed that this assumed aerosol driver is not compatible with the observed twentieth century North Atlantic variability. Also paleoclimate data (e.g. Delworth and Mann 2000; Gray et al. 2004; Chylek et al. 2011, 2012) showing a long time persistence of the AMO does not support an anthropogenic cause of the twentieth century AMO cycle.

Instead of relying on a particular model we consider three AMO scenarios that should bracket the possible range. In the first case we assume that the AMO cycle will not be significantly affected by increasing anthropogenic activities and that the next cycle will be similar to the one observed within the twentieth century with the cycle length of about 65 years (Schlesinger and Ramankutty 1994; Chylek et al. 2010). In this scenario the future AMO is a repetition of its past from the peak in 1943 (case [1] in Fig. 4a). As the second scenario we assume that the GHG

induced warming will destroy the AMO oscillating character and that in the future the AMO index will remain constant at its current value (case [2]). Finally in the third scenario the AMO index continues to grow similarly to its growth during the 1970–2010 time span (case [3] in Fig. 4a). Based on the past AMO experience (e.g. Delworth and Mann 2000; Gray et al. 2004; Chylek et al. 2011, 2012) we assign a high probability to the case of the AMO continuing its cyclic behavior with a cycle length of 60–70 years and a low probability to the case of AMO continuing to rise at its post 1975 rate.

These three AMO extensions (Fig. 4a) are combined with specified projections of GHGA and SOL, and our regression equation is used to obtain three projections for the future (up to 2050) US SW temperature (Fig. 4b). For comparison we also show the CMIP5 ensemble mean of the US SW temperature projection for the RCP4.5 pathway.

The repetition of the 65 year AMO cycle suggests the US SW temperature in 2050 to be close to its current value (case [1] in Fig. 4b). A constant AMO (case [2]) suggests warming of about 1 °C, while a continually increasing AMO (case [3]) leads to a warming of about 2 °C which is comparable to the CMIP5 ensemble mean projection.

5 Southwestern US precipitation

A similar regression analysis was performed on the southwestern US precipitation. The correlation coefficients between the US SW precipitation and individual explanatory variable are listed in Table 1. The usual set of climate influence variables (GHGA, SOL, VOLC, and ENSO) accounts only for 26 % of the precipitation variance (Table 3). Therefore we consider again the two additional predictors representing oceanic influences in the form of the AMO and PDO indices.

When all the predictors (GHGA, SOL, VOLC, ENSO, AMO, and PDO) are included the regression model accounts for 61 % of the observed precipitation variance, however, only the PDO, AMO and ENSO are statistically significant at $p = 0.05$ significance level (the PDO and AMO are statistically highly significant at $p < 0.01$).

We start our forward selection procedure with this pair of highly significant predictors (PDO and AMO) which accounts for 59 % of the observed US SW precipitation variance. Adding the ENSO to the set of explanatory variables increases the fraction of accounted for variance to 62 %, while all three predictors remain statistically significant. Adding any other combination of predictors to the PDO, AMO, and ENSO does not increase the accounted for fraction of variance beyond 62 %, and none of added predictors becomes statistically significant (Table 3). Thus

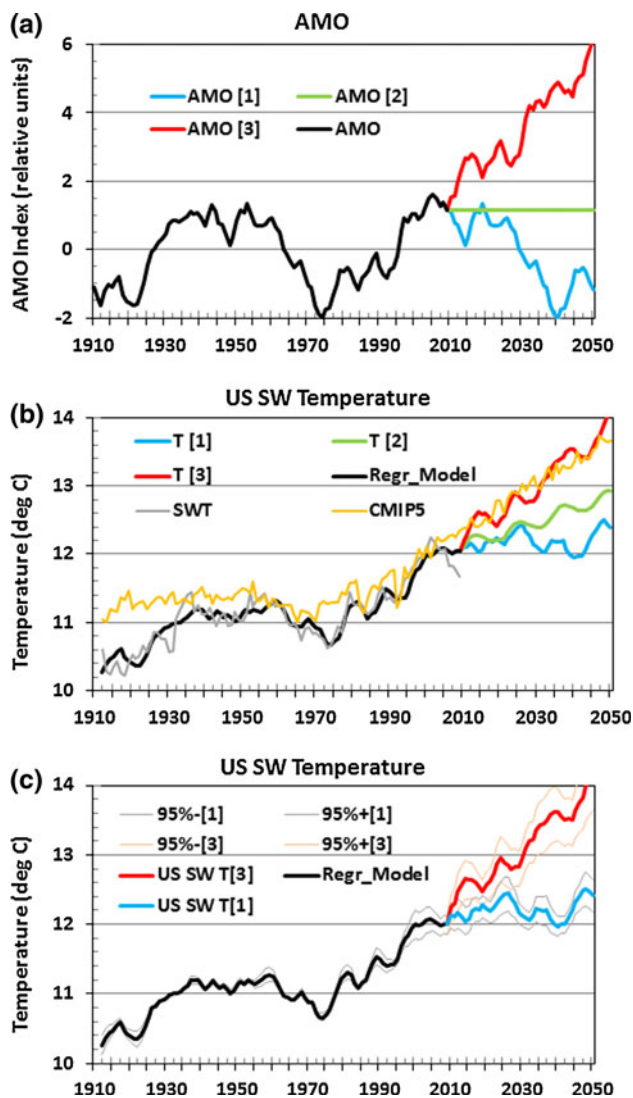


Fig. 4 **a** Instrumental era AMO (black), and three considered cases of its future projection: [1] repetition of the 65 year cycle (blue), [2] a constant at the present AMO value (green), and [3] continuation of the 1975–2010 increasing trend (red). **b** Regression reconstruction of the US SW temperature (black), and three different projections of the US SW temperature ([1], [2], [3]) based on the three considered AMO future projections. The observed US SW temperature (SWT gray) and the CMIP5 ensemble mean (yellow) with the RCM4.5 pathway are also shown. All data are the 5 year moving means. **c** 95 % confidence level (thin lines) for regression model and cases [1] and [3] of the temperature projection

we consider the set of three predictors (PDO, AMO, and ENSO) to be the most efficient set for regression analysis of the US SW precipitation. However, since we are interested to see an effect of anthropogenic greenhouse gases and aerosol on precipitation, we will also consider the predictor configuration with GHGA added to the set.

The observed precipitation of the southwestern US, its regression reconstruction and the ensemble mean of the CMIP5 models (decreased by 27 cm/year) are shown in

Table 3 Considered regression models of the US SW precipitation

n	k	SW precipitation predictors	R_{adj}^2
1	4	VOLC, ENSO, (SOL, GHGA)	0.26
2	2	PDO, AMO	0.59
3	3	PDO, AMO, ENSO	0.62
4	3	PDO, AMO, (SOL)	0.59
5	3	PDO, AMO, (VOLC)	0.60
6	3	PDO, AMO, (GHGA)	0.60
7	4	PDO, AMO, ENSO, (GHGA)	0.62
8	4	PDO, AMO, ENSO, (VOLC)	0.62
9	4	PDO, AMO, ENSO, (SOL)	0.62
10	6	PDO, AMO, ENSO, (GHGA, VOLC, SOL)	0.61

The n is the model number, k is the number of predictors in the given model, and R_{adj}^2 provides the fraction of the observed precipitation variance accounted for by the given model. The parenthesis around the acronym of an explanatory variable indicates that the predictor is not statistically significant at $p = 0.05$ significance level

Fig. 5a. Contributions of individual explanatory variables to the US SW precipitation for cases of three (PDO, AMO, and ENSO) and four (GHGA added to the three) predictors are shown in Fig. 5b, c. The partition of precipitation between the predictors is not sensitive to details of the final configuration of explanatory variables. Anthropogenic gases and aerosols have essentially no direct effect on the US SW precipitation (Fig. 5b). They can still affect the precipitation indirectly through their influence on the PDO and AMO, however, such effect if it exists is currently not understood. The highest $R_{adj}^2 = 0.62$ is common to the above stated three or four predictors as well as to other cases listed in Table 3.

Contributions of individual predictors provide an insight into the two recent drought episodes (1950s and 2010) of the US SW. In our four or three-predictor regression model (Fig. 5b, c) the main cause of the early drought (1950s) was related to a rapid decrease of the PDO contribution, while the AMO contribution was already close to its minimum for over a decade. The current drought is again produced by low values of both the PDO and AMO contributions, with the PDO contribution not yet as low as it was in 1950s. Also, the current drought is slightly moderated by a higher ENSO contribution compared to its 1950s value. The effect of anthropogenic GHGA was negligible during both dry periods.

6 PDO/AMO correlation

To estimate the future US SW precipitation using the above regression analysis we need to estimate the future values of the individual predictors. For the anthropogenic input (GHGA) we use the CMIP5 RCM4.5 pathway which is

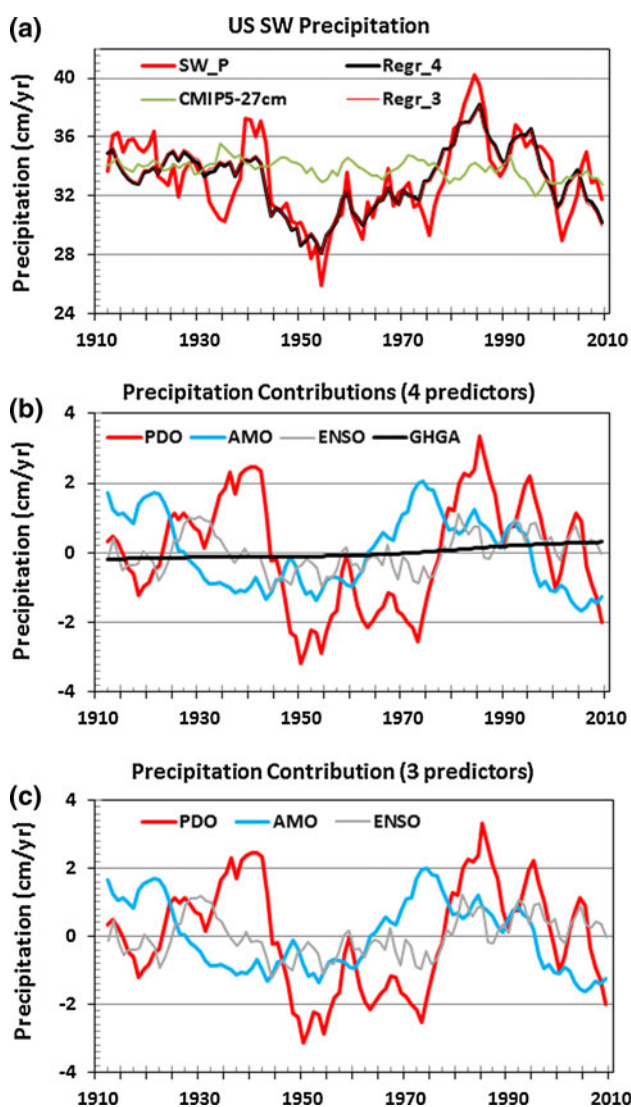


Fig. 5 a Observed US SW precipitation (*red*) compared to the four predictor regression model (*black*) and the ensemble mean of the CMIP5 models (*green*). The three predictor model (*thin red curve*) is visually indistinguishable from the four predictor model (*black*). b Contribution of four predictors to the US SW precipitation. c Contribution to the US SW precipitation from predictors of the three predictor regression model

designed to simulate a moderate rate of GHG increase. For ENSO we assume a cyclic repetition of its behavior from 1975 to 2010. Finally for the AMO we assume the same three alternatives as considered in Fig. 4a. Making an independent estimate of the future PDO is a problem. However, Wu et al. (2011b) noticed a lag anti-correlation between the PDO and AMO with the AMO index leading the PDO by about 12 years. Figure 6a presents the AMO/|PDO| correlation coefficients for PDO lag of up to 15 years. The maximum correlation is indeed observed at a 12 years lag with $r = 0.78$. The AMO and PDO (lagged by

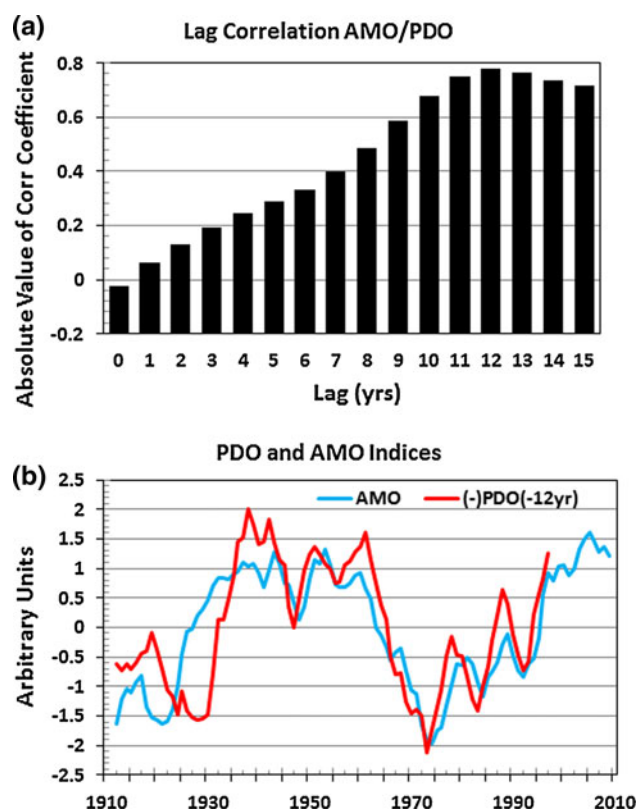


Fig. 6 a Lag correlation coefficients between the AMO and PDO. b Normalized AMO and PDO (with 12 years lag) indices

12 years) normalized indices (zero mean and unit variance) are shown in Fig. 6b. By using this relation, observed first by Wu et al. (2011b), we avoid the necessity to make an independent assumption concerning the future PDO index. We just replace the PDO index at year X by the AMO index with a lag of 12 years

$$PDO(X) = -AMO(X - 12) \tag{2}$$

and consider the three AMO cases as was done earlier (Fig. 4a). The physical processes responsible for this AMO/PDO connection are not yet understood (Wu et al. 2011b).

7 Future US SW precipitation

Using the above specified projection of the predictors needed for the US SW precipitation regression model, we can estimate the future precipitation. Figure 7 shows expected precipitation for the three cases of the AMO index. All three cases suggest a continuation of the present dry spell for the next few years (3–5). After that a decrease in the US SW precipitation (red curve in Fig. 7) occurs only in the case of the AMO index continuing to increase at

the rate similar to its 1970–2000 increase. A repetition of the AMO 60–70 year cycle observed during the twentieth century suggests a return to higher precipitation levels reaching a maximum around the year 2050 (blue curve in Fig. 7). A constant AMO index implies an almost constant precipitation (green curve in Fig. 7) close to the current value. Based on our earlier discussion and strong evidence for a cycling AMO long time before any significant anthropogenic influence, we assign a high probability to the case of an oscillating AMO which suggests an increase in US SW precipitation within the next few decades.

8 Discussion and conclusion

A multiple linear regression analysis of the twentieth century US SW climate suggests a strong oceanic influence on both the southwestern US temperature (from the AMO) and precipitation (from the PDO and AMO). About a half of the recent (post 1975) US SW warming trend can be attributed to the anthropogenic influences of increasing atmospheric concentration of greenhouse gases and aerosol variability (GHGA), with the remaining half being due to a positive phase of the AMO. The US SW precipitation has been dominated by oceanic influences (PDO and AMO) with no direct effect due to anthropogenic greenhouse gases and aerosols (GHGA). This of course does not exclude a possibility that the GHGA affects the AMO and PDO.

To estimate the future US SW climate evolution using the regression model we need to make an assumption concerning the future AMO behavior. The situation that we consider most likely is the repetition of a cyclic behavior that was observed during the twentieth century (Schlesinger and Ramankutty 1994) as well as during the

previous hundreds of years (Delworth and Mann 2000; Gray et al. 2004; Chylek et al. 2011, 2012). The regression model with a continuing AMO cyclic behavior suggests a stable temperature close to its present level and increasing precipitation within the next two to three decades.

A rising AMO index at the rate comparable to its 1975–2005 increase would bring harsh climatic conditions to the southwestern US. Projected temperature would increase by 2050 by about 2 °C above the current level (a warming similar to that predicted by the ensemble mean of the CMIP5 simulations) and precipitation would decrease by an additional 30 % compared to the current conditions. A strong warming and severe drought predicted on the basis of the ensemble mean of the CMIP climate models simulations (Seager et al. 2007; Williams et al. 2012) is supported by our regression analysis only in a very unlikely case of the continually increasing AMO at a rate similar to its 1970–2010 increase.

There is substantial evidence to support future AMO cyclic behavior. Instrumental records of central England temperature (Tung and Zhou 2013), tree rings (Delworth and Mann 2000; Gray et al. 2004) and ice core analysis (Meecker and Majewski 2002; Chylek et al. 2011, 2012; Henriksson et al. 2012) demonstrate the existence of the AMO cycles for many hundreds and possibly thousands of years when anthropogenic influences were negligible. Ice core analysis suggests a shorter AMO quasi-periodicity (about 20 years) during the Little Ice Age and a longer periodicity in the Medieval Warm Period (Chylek et al. 2012). Atmosphere–Ocean coupled climate models (Metha and Delworth 1995; Griffies and Bryan 1997; Delworth and Knutson 2000; Dong and Sutton 2001; Wei and Lohmann 2012; Mahajan et al. 2011; Henriksson et al. 2012; Yang et al. 2013; Escudier et al. 2013; Zanchettin et al. 2013) as well as simplified conceptual ocean models (Frankcombe and Dijkstra 2011), or statistical harmonic models (Humlum et al. 2011; Mazzarella and Scafetta 2012; Scafetta 2012) suggest a future persistent AMO like multi-decadal oscillation. Based on this evidence of the past behavior we expect the AMO to retain its cyclic behavior during the twenty-first century with a cycle length of 60–70 years.

It seems that the AMO index may have reached its peak around 2005 and started to turn downward (Fig. 4) but still in a positive AMO phase. Within a few years we should be able to see more clearly if this was a real turning point or only a temporary pause.

The US SW temperature and precipitation are strongly influenced by the AMO and PDO. The fact that the CMIP simulations ensemble mean can reproduce the 1970–2010 US SW temperature increase without inclusion of the AMO (the AMO is treated as an intrinsic natural climate variability that is averaged out by taking an ensemble mean of

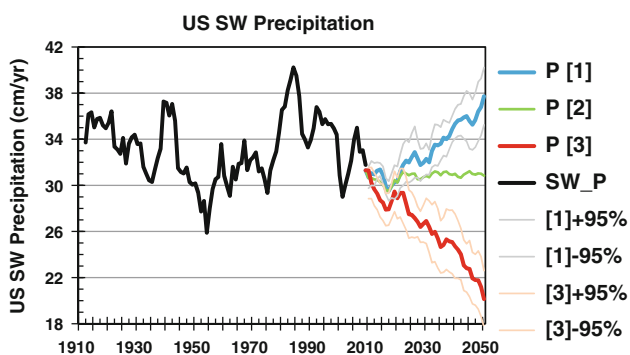


Fig. 7 Regression model projection of the US SW precipitation for the three cases of the assumed AMO behavior (Fig. 3a): [1] repetition of a 60–70 year cycle (blue), [2] constant AMO index (green), and [3] continuation of post 1975 rising trend (red). A 95 % confidence levels are shown for cases [1] and [3]

individual simulations) suggests that the CMIP5 models' predicted US SW temperature sensitivity to the GHG has been significantly (by about a factor of two) overestimated.

Acknowledgments Reported research (LA-UR-12-25073) was supported in part by the Los Alamos National Laboratory Institute of Geophysics, Planetary Physics, and Signatures.

Open Access This article is distributed under the terms of the Creative Commons Attribution License which permits any use, distribution, and reproduction in any medium, provided the original author(s) and the source are credited.

References

- Booth BB, Dunstone NJ, Halloran PR, Andrews T, Bellouin N et al (2012) Aerosols implicated as a prime driver of twentieth-century North Atlantic climate variability. *Nature* 484:228–232
- Cayan DR, Das T, Pierce DW, Barnett TP, Turee M, Gershunov A (2010) Future dryness in the southwest US and the hydrology of the early 21st century drought. *Proc Nat Acad Sci* 107: 21271–21276
- Chylek P, Folland CK, Lesins G, Dubey MK, Wang M (2009) Arctic air temperature change amplification and the Atlantic Multi-decadal Oscillation. *Geophys Res Lett* 36:L14801. doi:10.1029/2009GL038777
- Chylek P, Folland C, Lesins G, Dubey MK (2010) Twenties century bipolar seesaw of the Arctic and Antarctic surface air temperature. *Geophys Res Lett* 37:L08703. doi:10.1029/2010GL042793
- Chylek P, Folland CK, Dijkstra H, Lesins G, Dubey MK (2011), Ice-core data evidence for a prominent near 20 year time-scale of the Atlantic multi-decadal oscillation. *Geophys Res Lett* 38. L13704. doi:10.1029/2011GL047501
- Chylek P, Folland CK, Frankcombe L, Dijkstra H, Lesin G, Dubey MK (2012) Greenland ice core evidence for spatial and temporal variability of the Atlantic multi-decadal oscillation. *Geophys Res Lett* 39:L09705. doi:10.1029/2012GL051241
- Compo G, Sardeshmukh P (2009) Oceanic influences on recent continental warming. *Clim Dyn* 32:333–342
- Cook ER, Seager R, Heim RR, Vose RS, Herweijer C, Woodhouse C (2010) Megadrought in North America: placing IPCC projections of hydroclimate change in a long-term paleoclimate context. *J Quatern Sci* 25:46–61
- Dai A, Hu A, Meehl GA, Washington WM, Strand WG (2005) Atlantic thermohaline circulation in a coupled general circulation model: unforced versus forced changes. *J Clim* 18: 3270–3293
- Delworth T, Knutson T (2000) Simulation of early 20th century global warming. *Science* 287:2246–2250
- Delworth TL, Mann ME (2000) Observed and simulated multi-decadal variability in the Northern Hemisphere. *Clim Dyn* 16:661–676. doi:10.1007/s003820000075
- Dong B, Sutton T (2001) The dominant mechanism of variability in Atlantic ocean heat transport in a coupled ocean–atmosphere GCM. *Geophys Res Lett* 28:2445–2448
- Escudier R, Mignot J, Swingedouw D (2013) A 20-year coupled ocean–sea ice–atmosphere variability mode in the North Atlantic in an AOGCM. *Clim Dyn* 40:619–636
- Fawcett P et al (2011) Extended megadroughts in the southwestern United States during Pleistocene interglacials. *Nature* 470:518–521
- Foukal P (2012) A new look at solar variance irradiation. *Sol Phys* 279:365–381
- Frankcombe L, Dijkstra H (2011) The role of Atlantic–Arctic exchange in North Atlantic multi-decadal climate variability. *Geophys Res Lett* 38. doi:10.1029/2011GL048158
- Gray S, Graumlich L, Betancourt J, Pederson G (2004) A tree-ring based reconstruction of the Atlantic multi-decadal oscillation since 1567 AD. *Geophys Res Lett* 31:L12205. doi:10.1029/2004GL019932
- Griffies S, Bryan K (1997) A predictability study of simulated North Atlantic multi-decadal variability. *Clim Dyn* 13:459–487
- Henriksson S, Raisanen P, Silen J, Laaksonen A (2012) Quasiperiodic climate variability with a period of 60–80 years: Fourier analysis of measurements and earth system model simulations. *Clim Dyn* 39:1999–2011
- Humlum O, Solheim JE, Stordahl K (2011) Identifying natural contributions to late Holocene climate change. *Global Planet Chang* 79(1–2):145–156
- Keenlyside NS, Latif M, Jungclaus J, Kornblueh L, Roeckner E (2008) Advancing decadal-scale climate prediction in the North Atlantic sector. *Nature* 453:84–88
- Kerr RA (2013) Forecasting regional climate change flunks its first test. *Science* 339:638
- Knight J, Allan R, Folland C, Vellinga M, Mann M (2005) A signature of persistent natural thermohaline circulation cycle in observed climate. *Geophys Res Lett* 32. doi:10.1029/2005GL024233
- Knudsen MF, Seidenkrantz MS, Jacobsen BH, Kuijpers A (2011) Tracking the Atlantic multi-decadal oscillation through the last 8,000 years. *Nat Commun* 2. doi:10.1038/ncomms1186
- Kopp G, Lean JL (2011) A new, lower value of total solar irradiance: evidence and climate significance. *Geophys Res Lett* 38:L01706. doi:10.1029/2010GL045777
- Latif M, Roeckner E, Botzet M, Esch M, Haak H, Hagemann J, Jungclaus J, Legutke S, Marsland S, Mikolajewicz U, Mitchell J (2004) Reconstruction, monitoring and predicting multi-decadal-scale changes in the North Atlantic thermohaline circulation with sea surface temperature. *J Clim* 17:1605–1614
- Lean JL, Rind DH (2008) How natural and anthropogenic influences alter global and regional surface temperatures: 1889 to 2006. *Geophys Res Lett* 35:L18701. doi:10.1029/2008GL034864
- MacDonald GM (2010) Water, climate change, and sustainability in the southwest. *Proc Nat Acad Sci* 107:21256–21262
- Mahajan S, Zhang R, Delworth T (2011) Impact of the Atlantic meridional overturning circulation (AMOC) on arctic surface air temperature and sea ice variability. *J Clim* 24:6573–6581
- Mazzarella A, Scafetta N (2012) Evidence for quasi 60-year North Atlantic oscillation since 1700 and its meaning for global climate change. *Theor Appl Climatol* 107:599–609. doi:10.1007/s00704-0499-4
- Meeker L, Majewski P (2002) A 1400-year high-resolution record of atmospheric circulation over the North Atlantic and Asia, year high-resolution record of atmospheric circulation over the North Atlantic and Asia. *Holocene* 12:257–266
- Metha V, Delworth T (1995) Decadal variability of the tropical Atlantic–ocean surface–temperature in shipboard measurements and in global ocean–atmosphere model. *J Clim* 8:172–190
- North GR (1975) Theory of energy-balance climate models. *J Atmos Sci* 32:2033–2043
- Oglesby R, Feng S, Rowe C (2012) The role of the Atlantic multi-decadal oscillation on medieval drought in North America: synthesizing results from proxy data and climate models. *Global Planet Chang* 84–85:56–65
- Polyakov I, Johnson M (2000) Arctic decadal and interdecadal variability. *Geophys Res Lett* 27:4097–4100

- Scafetta N (2012) Multi-scale harmonic model for solar and climate cyclical variation throughout Holocene based on Jupiter-Saturn tidal frequencies plus the 11-year solar dynamo cycle. *J Atmos Solar-Terrest Phys* 80:296–311. doi:[10.1016/j.jastp.2012.02.016](https://doi.org/10.1016/j.jastp.2012.02.016)
- Schlesinger ME, Ramankutty N (1994) An oscillation in the global climate system of period 65–70 years. *Nature* 367:723–726. doi:[10.1038/367723a0](https://doi.org/10.1038/367723a0)
- Seager R, Ting M, Held I, Kushnir Y, Lu J, Vecchi G, Huang H-P, Harnik L, Leetma A, Lau N-C, Li C, Velez J, Naik N (2007) Model projections of an imminent transition to a more arid climate in southwestern North America. *Science* 316:1181–1184
- Semenov VA, Latif M, Dommenges D, Keenlyside NS, Strehz A, Martin T, Park W (2010) The impact of North Atlantic–Arctic multi-decadal variability on Northern Hemisphere surface air temperature. *J Clim* 23(21):5668–5677
- Solomon S, et al (2007) *Climate change 2007: working group I. The Physical Science Basis*, Cambridge, 996 pp
- Solomon A et al (2011) Distinguishing the role of natural and anthropogenically forced decadal climate variability. *Bull Am Meteor Soc* 92:141–156
- Ting M, Kushnir Y, Saeger R, Li C (2009) Forced and internal twentieth-century SST trends in the North Atlantic. *J Clim* 22:1469–1481
- Touchan R, Woodhouse CA, Meko DM, Allen C (2011) Millennial precipitation reconstruction for the Jemez Mountains, New Mexico, reveals changing drought signal. *Int J Climatol* 31: 896–906
- Tung KK, Zhou J (2013) Using data to attribute episodes of warming and cooling in instrumental records. *Proc Natl Acad Sci USA* 110:2058–2063
- van Oldenborgh G, Doblas Reyes F, Drijfhout S, Hawkins E (2013) Reliability of regional climate model trends. *Environ Res Lett* 8. doi:[10.1088/1748-9326/8/1/014055](https://doi.org/10.1088/1748-9326/8/1/014055)
- Vernier JP et al (2011) Major influence of tropical volcanic eruptions on the stratospheric aerosol layer during the last decade. *Geophys Res Lett* 38:L12807. doi:[10.1029/2011GL047563](https://doi.org/10.1029/2011GL047563)
- Wei W, Lohmann G (2012) Simulated Atlantic multi-decadal oscillation during the Holocene. *J Clim* 25:6989–7002
- Wilks DS (2006) *Statistical Methods in the Atmospheric Sciences*. Academic Press, New York
- Williams A, et al (2012) Temperature as a potent driver of regional forest drought stress and tree mortality. *Nat Clim Chang*. doi:[10.1038/NCLIM1693](https://doi.org/10.1038/NCLIM1693)
- Woodhouse CA, Meko DM, MacDonald GM, Stahle DW, Cooke ER (2010) A 1,200-year perspective of 21st century drought in southwestern North America. *Proc Nat Acad Sci* 107: 21283–21288
- Wu Z, Huang NE, Long SR, Peng CK (2007) On the trend, detrending, and variability of nonlinear and nonstationary time series. *Proc Natl Acad Sci USA* 104:14889–14894
- Wu S, Liu Z, Zhang R, Delworth T (2011a) On the observed relationship between the Pacific decadal oscillation and the Atlantic multi-decadal oscillation. *J Oceanogr* 67:27–35. doi:[10.1007/s10872-011-0003-x](https://doi.org/10.1007/s10872-011-0003-x)
- Wu Z, Huang NE, Wallace JM, Smoliak B, Chen X (2011b) On the time-varying trend in global mean surface temperature. *Clim Dyn* 37:759–773
- Wyatt M, Kratsov S, Tsonis A (2011) Atlantic multi-decadal oscillation and Northern Hemispheres climate variability. *Clim Dyn*. doi:[10.1007/s00382-011-1071-8](https://doi.org/10.1007/s00382-011-1071-8)
- Yang X et al (2013) A predictable AMO-like pattern in the GFDL fully coupled ensemble initialization and decadal forecasting system. *J Clim* 26:650–661
- Zanchettin D, Rubino A, Matei D, Bothe O, Jungclaus J (2013) Multi-decadal-to-centennial SST variability in the MPI-ESM simulation ensemble for the last millennium. *Clim Dyn* 40:1301–1318
- Zhang R, Delworth TL, Held IM (2007) Can the Atlantic Ocean drive the observed multi-decadal variability in Northern Hemisphere mean temperature? *Geophys Res Lett* 34:L02709. doi:[10.1029/2006GL028683](https://doi.org/10.1029/2006GL028683)
- Zhang R et al (2013) Have aerosols caused the observed Atlantic multi-decadal variability? *J Atmos Sci*. doi:[10.1175/JAS-D-12-0331.1](https://doi.org/10.1175/JAS-D-12-0331.1)
- Zhou J, Tung KK (2013) Deducing multi-decadal anthropogenic warming trends using multiple regression analysis. *J Atmos Sci* 70:3–8