AGU PUBLICATIONS

Geophysical Research Letters

RESEARCH LETTER

10.1002/2017GL075905

Key Points:
- This study quantifies for the first time the multidecadal influence of sea surface temperature on variability in U.S. air quality
- Summertime air quality in the eastern United States degrades in the warm phase of the Atlantic Multidecadal Oscillation (AMO)
- An AMO shift to the cold phase in future years could partly offset the climate penalty on U.S. air quality brought by global warming

Supporting Information:
- Supporting Information S1

Correspondence to:
L. Shen,
lshen@fas.harvard.edu

Citation:
Shen, L., Mickley, L. J., Leibensperger, E. M., & Li, M. (2017). Strong dependence of U.S. summertime air quality on the decadal variability of Atlantic sea surface temperatures. *Geophysical Research Letters*, *44*. https://doi.org/10.1002/2017GL075905

Received 2 OCT 2017
Accepted 7 DEC 2017
Accepted article online 13 DEC 2017

Strong Dependence of U.S. Summertime Air Quality on the Decadal Variability of Atlantic Sea Surface Temperatures

Lu Shen[1], Loretta J. Mickley[1], Eric M. Leibensperger[2], and Mingwei Li[3]

[1]John A. Paulson School of Engineering and Applied Sciences, Harvard University, Cambridge, MA, USA, [2]Center for Earth and Environmental Science, SUNY Plattsburgh, Plattsburgh, NY, USA, [3]Department of Earth, Atmospheric and Planetary Sciences, Massachusetts Institute of Technology, Cambridge, MA, USA

Abstract We find that summertime air quality in the eastern U.S. displays strong dependence on North Atlantic sea surface temperatures, resulting from large-scale ocean-atmosphere interactions. Using observations, reanalysis data sets, and climate model simulations, we further identify a multidecadal variability in surface air quality driven by the Atlantic Multidecadal Oscillation (AMO). In one-half cycle (~35 years) of the AMO from cold to warm phase, summertime maximum daily 8 h ozone concentrations increase by 1–4 ppbv and $PM_{2.5}$ concentrations increase by 0.3–1.0 $\mu g\ m^{-3}$ over much of the east. These air quality changes are related to warmer, drier, and more stagnant weather in the AMO warm phase, together with anomalous circulation patterns at the surface and aloft. If the AMO shifts to the cold phase in future years, it could partly offset the climate penalty on U.S. air quality brought by global warming, an effect which should be considered in long-term air quality planning.

1. Introduction

Accurate forecasts of future air quality are necessary for long-term regulatory efforts, especially as the cost of reducing anthropogenic emissions keeps increasing (Pappin et al., 2015). Because air quality is strongly tied to weather (Jacob & Winner, 2009), knowledge of the magnitude of climate variability is essential to such forecasts. Instrumental records show marked multidecadal variability in climate in North America (McCabe et al., 2004; Nigam et al., 2011; Sutton & Hodson, 2005, 2007). The potential impact of such variability on air quality has been noted in previous modeling studies (e.g., Barnes et al., 2016; Garcia-Menendez et al., 2017) but still needs to be verified and quantified. In 2015, the U.S. Environmental Protection Agency strengthened the National Ambient Air Quality Standards for surface ozone from 75 ppbv to 70 ppbv. Key questions are whether a more stringent standard will be necessary against the background of global warming and to what extent multidecadal variability in climate will hamper efforts to meet air quality goals.

Ozone and fine particulate matter ($PM_{2.5}$) are two key air pollutants with large impacts on public health in industrialized and developing regions around the world (Lelieveld et al., 2015). U.S. ozone and $PM_{2.5}$ concentrations have generally declined in recent years due to emission controls (Bloomer et al., 2009; Cooper et al., 2012; Hu et al., 2014), but meteorological factors such as temperature may still degrade air quality and lead to extreme pollution events, putting public health at risk (Fiore et al., 2015; Jacob & Winner, 2009). Many studies have quantified the strong dependence of air quality on regional-scale meteorology (Leibensperger et al., 2008; Shen, Mickley, & Tai, 2015; Shen, Mickley, & Gilleland, 2016; Shen & Mickley, 2017; Tai et al., 2012). On the seasonal timescale, summertime ozone concentrations in the eastern United States also display a statistically significant relationship with the North Atlantic sea surface temperatures (SSTs) (Shen, Mickley, & Murray, 2017). This implies that large-scale phenomena such as the Atlantic Multidecadal Oscillation (AMO) may influence multidecadal variability in U.S. air quality; an effect will be investigated in this study.

2. Data and Methods

2.1. Data Used in This Study

Site measurements of ozone (1980–2015) and $PM_{2.5}$ (1999–2015) are obtained from EPA Air Quality System (EPA-AQS, http://www.epa.gov/ttn/airs/airsaqs/), and interpolated onto a 2.5° × 2.5° latitude-by-longitude grid resolution (Shen, Mickley, & Tai, 2015; Shen & Mickley, 2017). We use meteorological data from the National Centers for Environmental Prediction (NCEP) Reanalysis 1 (Kalnay et al., 1996). For the historical meteorology since the late nineteenth century, we use different meteorological variables from a variety of sources, including (i) temperature data from U.S. climate divisions from National Climatic Data Center (Vose et al., 2014), Gridded Historical Climatology Network (GHCN, v3) provided by NOAA/Oceanic and Atmospheric Research/Earth System Research Laboratory Physical Sciences Division, University of Delaware, air temperature and precipitation data set (Willmott et al., 2001), Merged Land-Ocean Surface Temperature Analysis (MLOST) (Smith et al., 2008; Vose et al., 2012), Jones (CRU) Air Temperature Anomalies Version 4 (CRUTEM4) (Jones et al., 2012), (ii) precipitation data from National Climate Data Center (NCDC), Global Precipitation Climatology Centre (GPCC) (Schneider et al., 2011), GHCN (v2), and University of Delaware air temperature and precipitation data set, (iii) sea level pressure from Hadley Centre sea level pressure data set (HadSLP2, Allan & Ansell, 2006), and (iv) different drought indices from NCDC. A more complete list can be found in Table S1.

As part of this study, we use the NOAA-CIRES Twentieth Century Reanalysis (NOAA-20CR) and European Centre for Medium-Range Weather Forecasts (ECMWF) Twentieth Century Reanalysis (ERA-20CM). The NOAA-20CR product assimilates only surface pressure and using SST and sea ice distributions as boundary conditions (Compo et al., 2011). The ERA-20CM product is constructed using SST and sea ice distributions as boundary conditions and forcings from Coupled Model Intercomparison Project Phase 5 (CMIP5) recommendations, without assimilating any other variables (Hersbach et al., 2015).

2.2. Definition of Heatwave, Stagnation Days, and AMO

We define a heatwave as two consecutive days with daily mean temperatures exceeding the 95th percentile of all summertime daily mean temperatures for that grid cell or site from 1900 to 2010 (Anderson & Bell, 2011). We classify a day as stagnant when the daily mean near-surface wind speed is less than 3.2 m s^{-1}, daily mean midtropospheric wind speed is less than 13 m s^{-1}, and daily accumulated precipitation is less than 1 mm (Horton & Diffenbaugh, 2012).

We define the AMO using SSTs from Hadley Centre Sea Ice and Sea Surface Temperature (HadISST1) data set (Rayner et al., 2003). We first remove high-frequency fluctuations in the 1895–2015 time series of summer mean global SSTs outside the North Atlantic (0–60°N, 75°W–7.5°W) by applying a low-pass filter. More specifically, we use locally weighted scatterplot smoothing (lowess) with a smoothing parameter of $\frac{2}{3}$ (Cleveland, 1981) to obtain the low-frequency variability. We next define an AMO index as the summer mean difference between average North Atlantic SSTs and average low-pass-filtered SSTs between 60°S and 60°N, and then removing the long-term mean. Unlike many previous studies (Sutton & Hodson, 2005, 2007), we define AMO using summertime mean SSTs rather than annual means. We take this approach because June-July-August (JJA) mean AMO shows better correlation with summertime temperature in the eastern United States, despite the fact that the 11 year running mean JJA AMO highly correlates with annual AMO ($r = 0.97$, Figure S1 in the supporting information). The time series of summertime AMO index in this study also matches those using other definitions or SST data sets, as shown in Figure S2 (Kennedy et al., 2011; Trenberth & Shea, 2006; Van Oldenborgh et al., 2009).

2.3. Goddard Institute for Space Studies Simulations

We smooth the AMO time series by applying an 11 year moving average and then standardizing the AMO index to zero mean with unit variance. Following the method in previous studies (Sutton & Hodson, 2005, 2007), we then regress the 1900–2012 annual mean SSTs in each grid box onto the standardized and smoothed AMO index, yielding the SST sensitivity to unit change of AMO. We apply this regression only to those grid boxes within the northern Atlantic (0–60°N), the region we show has a strong influence on U.S. surface temperatures. This procedure produces a map of SST anomalies in the northern Atlantic associated with the positive phase of an idealized AMO (Figure S3). We scale the resulting patterns of positive and negative mean AMO SSTs by a factor of 4 and apply these patterns to the Goddard Institute for Space Studies (GISS) ModelE2 (Sutton & Hodson, 2005, 2007). With the external forcing amplified by this scaling, the climate model can reach equilibrium with a shorter integration time. The model is integrated for 21 years with the first year discarded. To compare with the observations, we rescale the modeled meteorological anomalies as simulated in the GISS model by 0.25.

2.4. Statistical Methods to Calculate $PM_{2.5}$ Concentrations, MDA8 Ozone, and Ozone Episodes

For both $PM_{2.5}$ and MDA8 ozone, we apply a multivariate linear regression model using observed relationships between these pollutants and local meteorology as well as synoptic circulation patterns, as developed in Shen and Mickley (2017). We construct the synoptic circulation factors through the use of singular value decompositions of the spatial correlations between $PM_{2.5}$ (or MDA8 ozone) in each grid box and meteorological variables in grid boxes in the surrounding region. More details about this model can be found in Text S1. Using leave-one-out cross validation, we find that the coefficients of determination (R^2) between observed and predicted values range from 0.4 to 0.7 for JJA MDA8 ozone from 1980 to 2015 and 0.3 to 0.6 for $PM_{2.5}$ from 1999 to 2015 (Figure S4). When averaged across the eastern United States, the R^2 is 0.60 for ozone and 0.41 for $PM_{2.5}$.

We use the hybrid extreme value theory (hybrid-EVT) model to simulate ozone extremes (>70 ppbv) conditionally on daily mean temperature (Shen, Mickley, & Tai 2015). Ozone suppression, defined as a marked decrease in the ozone-temperature slope at high temperatures, occurs at ~20% U.S. sites (Shen, Mickley, & Gilleland, 2016). Our hybrid-EVT model thus consists of two parts: a point process model to simulate the extreme tails and a logistic regression and a Generalized Pareto Distribution model to capture the observed ozone suppression (Shen, Mickley, & Gilleland, 2016; Coles, 2001). We define an ozone episode day as those days when MDA8 ozone is greater than 70 ppbv.

2.5. Calculation of the Changes in Temperature and Air Quality in One-Half AMO Cycle

We calculate the changes of temperature and surface air quality in one-half cycle of AMO as follows, using JJA MDA8 ozone as an example. First, we calculate the JJA seasonal mean MDA8 ozone for each year from 1895 to 2015 by applying the statistical regression model to meteorological observations and different reanalysis data sets. Second, we calculate the slopes by regressing the time series of ozone concentration onto the AMO index. Third, we multiply the slopes by 0.49 K, the maximum observed change in the 11 year moving averaged AMO index in one-half cycle over the twentieth century. We define this value as the maximum change of ozone concentrations in one-half cycle of AMO. More details about this methodology can be found in Figure S5.

The changes in air quality in GISS ModelE over one-half cycle of AMO are calculated in two steps. For example, for ozone, we first predict JJA ozone concentrations in each summer by applying our statistical model to GISS simulated meteorology. We next calculate the climatological mean difference in ozone between the warm and cold phase of the AMO, which corresponds to the response of ozone to 2 standard deviations (or 0.29 K) of changes in the AMO index. Finally, we calculate the change in ozone over the eastern United States in one-half AMO cycle by multiplying the climatological mean difference in ozone by a factor of 1.68 (0.49 K/0.29 K = 1.68).

3. Strong Dependence of U.S. Summertime Climate and Air Quality on Atlantic SSTs

Summertime temperature in the eastern United States (100°W–75°W, 30°N–50°N, Figure 1a) is closely linked to Atlantic SSTs (Sutton & Hodson, 2005, 2007). After detrending, we find that the 11 year running mean June-July-August (JJA) temperature in the eastern United States from 1895 to present is correlated with these large-scale climate patterns: warm SSTs anomalies spanning the North Atlantic Ocean (Figure 1a) and negative sea level pressure (SLP) anomalies over North America and the North Atlantic as well as positive SLP anomalies over the central northeast Pacific (Figure 1b). These correlations arise because the adiabatic heating over the North Atlantic can induce ascent in that region and leads to low SLPs extending from the Atlantic across North America (Sutton & Hodson, 2005, 2007), a pattern similar to Figure 1b. This vertical motion can induce cyclonic circulation in the lower troposphere over North America and anticyclonic circulation aloft, a pattern associated with increased summertime temperatures in the United States (Sutton & Hodson, 2005, 2007).

We find that summertime air quality in the eastern United States, like temperature, also shows a strong dependence on SST patterns, at least over the relatively short time records of observations for ozone (1980–2015) and $PM_{2.5}$ (1999–2015). Figures 1c and 1d show the correlations of mean JJA surface air temperature and maximum daily 8 h average (MDA8) ozone, detrended and averaged over the East, with SSTs. Given the strong correlation of ozone and temperature in the East (Figure S6a), it is not surprising that

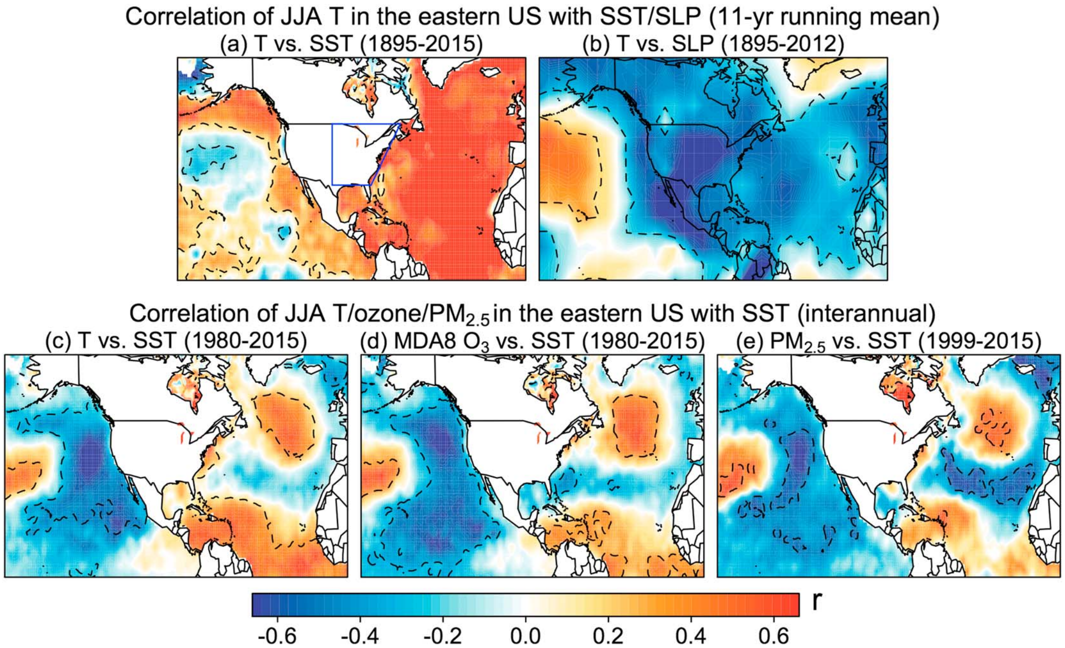

Figure 1. Correlations of JJA temperature in the eastern United States with (a) seasonal mean SSTs and (b) SLPs from 1895 to present. All time series in Figures 1a and 1b are linearly detrended for 1895–2015 and then smoothed with an 11 year moving average filter before calculating the correlation coefficient. (c) Same as Figure 1a, but for interannual correlations over 1980–2015. (d and e) Same as (c), but for (d) 1980–2015 JJA MDA8 ozone and (e) 1999–2015 JJA surface $PM_{2.5}$ concentrations. The blue quadrangle in Figure 1a indicates the domain of the eastern United States. The dashed contour lines enclose regions in which the correlations reach statistical significance ($p < 0.05$). All data in Figure 1c–1e are detrended by subtracting the 7 year moving averages. Figures 1c and 1d are redrawn from Figures 4b and 1c in Shen and Mickley (2017) with updated observations.

these variables display similar patterns of correlation with SSTs: a tripole mode in the Atlantic Ocean with significant positive correlations in the tropics and high latitudes but slightly negative correlations in the midlatitudes, and a dipole mode in the northeastern Pacific Ocean, with negative correlations stretching along the west coast of North America and positive correlations in the central Pacific. The tripole mode in the Atlantic implies that warm SSTs there are associated with warmer summers as well as enhanced ozone in the eastern United States (Shen, Mickley, & Murray, 2017). The dipole mode in the Pacific resembles the Pacific extreme pattern, which is associated with an eastward propagating flux in wave activity that promotes more frequent heat waves in the eastern United States (McKinnon et al., 2016), and enhanced ozone concentrations (Shen, Mickley, & Murray, 2017, Figure 1d). The Pacific dipole mode is significant only on interannual time scales (Figure 1c), but disappears when we apply an 11 year running mean filter to the time series (Figure 1a). Over 1999–2015, mean JJA concentrations of $PM_{2.5}$ in the eastern United States exhibit a dependence on SSTs patterns similar to those for ozone and temperature, with a tripole mode in the Atlantic and a dipole mode in the northeast Pacific. This dependence arises from strong correlations between JJA $PM_{2.5}$ concentrations and surface air temperatures (Figure S6b) in the east (Shen, Mickley, & Murray, 2017). Similar correlation patterns are obtained using different SST data sets (Figure S7), suggesting that the dependence of air quality in the eastern United States on SST patterns is a robust feature.

Multidecadal SST variability in the North Atlantic is dominated by the AMO. Summertime instrumental records show that the AMO warm phase occurred during the 1926–1960 and 1997–2015 time periods; the cold phase occurred during 1900–1925 and 1961–1996 (Figure 2a) (Sutton & Hodson, 2005). Using JJA temperature data from the National Climate Data Center (NCDC), we find that these temperatures averaged over the eastern United States show positive anomalies in warm AMO and negative anomalies in cold AMO (Figure 2a). Expressed as 11 year running means, these two time series correlate, with $r = 0.82$ ($p < 0.05$). To characterize the climate variations associated with the AMO, we calculate the change in summertime variables in one-half AMO cycle—that is, the average change from the trough in a cold phase to the peak in a warm phase, as described in section 2. In one-half AMO cycle, temperatures show significant warming over the eastern United States (0–0.8 K) and Great Plains (0.6–1.2 K), but less warming in the deep south (0–0.4 K) (Figure 2b). The spatial pattern of sensitivity is consistent across observation analysis data sets (Figures S8a–S8d).

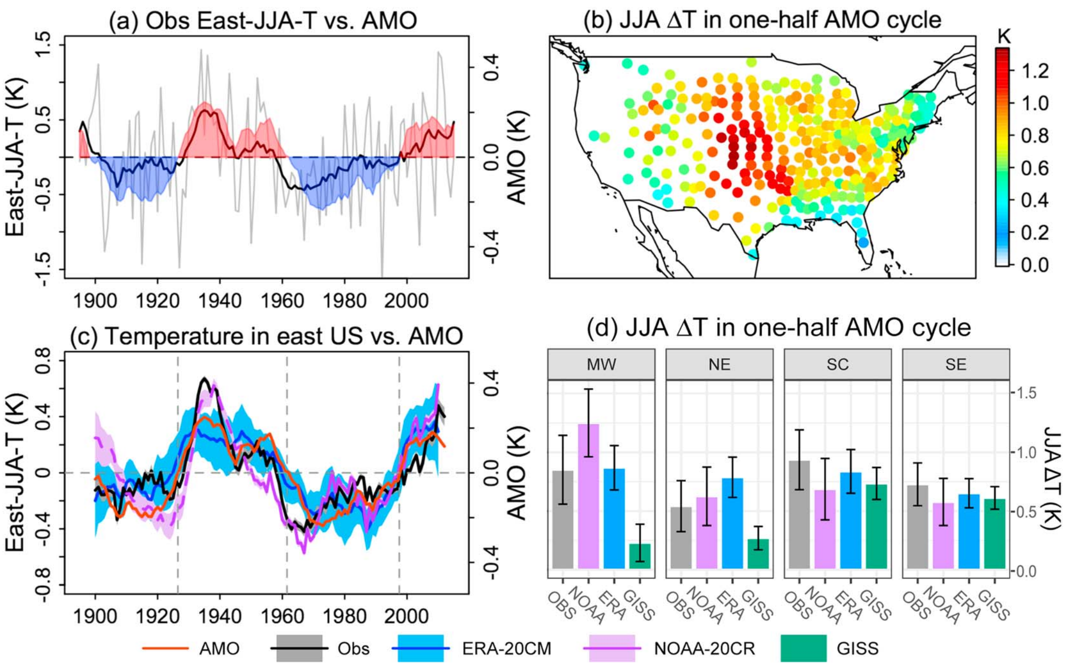

Figure 2. (a) The 11 year running mean AMO index (shaded red and blue areas) and linearly detrended NCDC JJA surface air temperature (black line) in the eastern United States from 1895 to 2015. The gray line denotes the JJA air temperatures in each year. (b) Changes ($p < 0.05$) of mean JJA temperature in the United States in one-half AMO cycle. (c) The 11 year running mean time series of JJA temperature, averaged over the eastern United States, together with AMO index, from 1900 to 2012. "Obs" signifies the mean of all observed temperature data sets listed in Table S1; modeled data sets are also defined in Table S1. All temperature time series have been detrended via linear regression. Temperature anomaly in NOAA-20CR from 1900 to 1950 is twice that of NCDC. To reduce this bias, we scale the NOAA-20CR temperature anomaly by a factor of 0.5 before 1950, denoted by the dashed line. Shaded areas denote one standard deviation across ensemble members. (d) Regional changes of JJA temperature in one-half AMO cycle in midwest (MW), northeast (NE), south central (SC), and southeast (SE). The geographical domains are shown in Figure S9. Error bars denote one standard deviation.

We next investigate whether the temperature variability in the eastern United States, shown in Figures 2a and 2b, arises in response to ocean fluctuations or to atmospheric variability that also drives SST variability. We begin by examining the impacts of AMO on meteorological variables such as temperature and precipitation from a variety of data sets (Table S1), including site-based measurements and indices derived from these measurements, the National Oceanic and Atmospheric Administration Twentieth Century Reanalysis (NOAA-20CR), and the ECMWF Twentieth Century Reanalysis (ERA-20CM). The NOAA-20CR product is constructed by assimilating only surface pressure and using SST and sea ice distributions as boundary conditions (Compo et al., 2011); it reflects the impacts arising from variability in both the ocean and atmosphere. The ERA-20CM product is constructed using only SST and sea ice distributions as boundary conditions and forcing terms from the CMIP5 recommendations. Since it does not assimilate any atmospheric observations, ERA-20CM is not able to reproduce synoptic circulations (Hersbach et al., 2015). Using GISS ModelE2 (Schmidt et al., 2014), we also simulate the effects of AMO on the climate as obtained by driving the model with idealized Atlantic SST patterns in the warm and cold AMO (Sutton & Hodson, 2005, 2007).

The data sets in Table S1 confirm that a warm AMO favors a warmer summer in the eastern United States. Figure 2c compares the time series of 11 year running mean JJA temperatures simulated by NOAA-20CR and ERA-20CM in the eastern United States with the AMO index for 1900–2010. The correlation coefficient r with AMO is 0.72 for NOAA-20CR and 0.90 for ERA-20CM, suggesting that it is the warmer Atlantic that drives a warmer summer in the United States. In one-half cycle of AMO, these two products show a spatial pattern of changes similar to that observed, except that NOAA-20CR displays a much stronger response, up to 1.5 K warming in the Great Plains (Figures S8e and S8f). Driven by prescribed SSTs related to AMO, the GISS model predicts larger changes in the south (+0.4–0.9 K) but smaller changes (+0.2–0.5 K) in the north (Figure S8g). These regional impacts, including those in the midwest, northeast, south central, and southeast (Figure S9), are summarized in Figure 2d. Consistent with previous studies (Hodson et al., 2010; Kumar et al., 2013; Kunkel et al., 2006; Sutton & Hodson, 2005, 2007), our results suggest that fluctuations in SSTs contribute to a large fraction of the multidecadal variability of summertime temperature in the eastern United States.

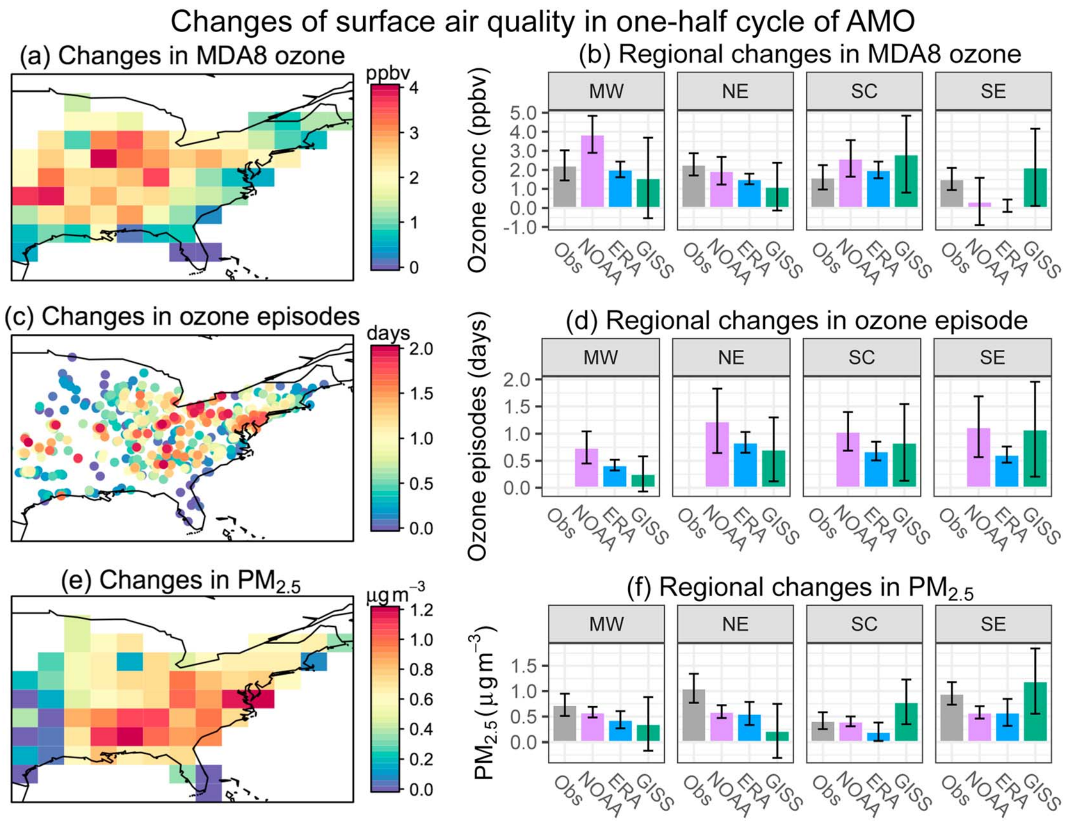

Figure 3. Calculated changes of summertime (a) MDA8 ozone, (c) ozone episode number (>70 ppbv) per summer, and (e) surface $PM_{2.5}$ in one-half AMO cycle from cold to warm phase. The panels show the average results obtained from four different data sets (see section 2 and Figure S5). (b, d, and f) These pollutant changes by region: midwest (MW), northeast (NE), south central (SC), and southeast (SE), as defined in Figure S9. "Obs" signifies results obtained using observed meteorology, including MLOST temperatures, winds derived from HadSLP2 sea level pressures, and GPCC precipitation. Other data sets are defined in Table S1. Error bars denote one standard deviation. For all panels, the effects on 1900–1950 surface air quality obtained from the NOAA-20CR data set are scaled by a factor of 0.5.

Like JJA average temperatures, the number of heatwaves per summer increases by 1–3 days in the eastern United States during warm AMO (Figures S10a and S10b). The number of stagnation days per summer also increases by 0.5–1 days during warm AMO (Figures S10c and S10d), with implications for pollution episodes (Leibensperger et al., 2008). Instrumental records also show that the warm AMO phase is associated with much drier summers, with precipitation deficits of 0.2–0.7 mm d^{-1} over the Great Plains (Figure S11) and more severe drought across much of the east and Intermountain West (Figure S12). Taken together, these changes are associated with anomalous cyclonic circulation at the surface and with decreased SLPs over the North America and North Atlantic (Figure S13), as well as an anticyclonic circulation anomaly aloft (Figure S14), consistent with previous results (Hodson et al., 2010; Sutton & Hodson, 2005, 2007).

4. Multidecadal Variability of Summertime Air Quality in the Eastern United States

The strong dependence of ozone and $PM_{2.5}$ concentrations on meteorological conditions implies that the AMO likely also drives multidecadal variability in U.S. air quality. The history of air pollutant observations, however, is short, with ~36 years for ozone (since 1980) and just ~17 years for $PM_{2.5}$ (since 1999), making it impossible to observe such multidecadal variability directly. To overcome this challenge, we attempt to predict ozone and $PM_{2.5}$ concentrations from meteorological variables over the twentieth century, assuming present-day emissions. In many previous studies, chemical transport models or chemistry climate models have been used to simulate air quality on long timescales (Fiore et al., 2015), but such models have difficulties capturing present-day variability in ozone (Doherty et al., 2013; Fiore et al., 2009) and $PM_{2.5}$ (Shen & Mickley, 2017). The high computation expense also restricts the use of these models to simulate long-term (>30 years) air quality variability.

An alternative method to predict ozone and $PM_{2.5}$ over long timescales is to use a statistical approach (Shen, Mickley, & Gilleland, 2016, Shen & Mickley, 2017), as displayed in Figure S5. By applying observed, present-day relationships between these pollutants and meteorological variables to a suite of observations and historical reanalysis data sets, we can bypass many of the uncertainties inherent in the climate projections. Such calculations assume that anthropogenic emissions remain at present-day levels. We emphasize that the goal of this exercise is not to hindcast ozone and $PM_{2.5}$ over the twentieth century but to diagnose the sensitivity of these pollutants to AMO variation. We focus primarily on the changes of air quality in one-half AMO cycle (~35 years).

Our analysis identifies a multidecadal, AMO-driven variability in both ozone and $PM_{2.5}$ air quality in the eastern United States. In one-half cycle of AMO from the cold to warm phase, MDA8 ozone concentrations increase 2–4 ppbv over most of the east (Figures 3a and 3b), with the largest increase of 3–4 ppbv over the Great Plains, where temperature rises the most (Figures S8 and S15a). The number of ozone episodes per summer increases by 1–3 days, with the largest increases of 2–3 days at many sites in the northeast and southeast (Figures 3c and 3d). We find that those sites having the most frequent ozone episodes in the present day (Shen, Mickley, & Gilleland, 2016) are also the most vulnerable to increases in such episodes in the warm phase of AMO. $PM_{2.5}$ concentrations increase by 0.2–1 $\mu g\ m^{-3}$ in the eastern United States over one-half cycle of AMO, with the largest increase of 0.6–1 $\mu g\ m^{-3}$ in the northeast and southeast and also slight increases over the Great Plains (Figures 3e and 3f). This pattern of response reflects the greater sensitivity of $PM_{2.5}$ to temperature change in the northeast and southeast than in other regions (Shen, Mickley, & Murray, 2017), as implied in Figure S15b. In sum, the warm phase of AMO degrades both ozone and $PM_{2.5}$ air quality in the eastern United States and also drives up ozone episode number in this region. Increases in pollutant concentrations can have consequences for human health, following the method of Shindell et al. (2016). More details can be found in Text S2 (Anenberg et al., 2012; Jerrett et al., 2009; Pope et al., 2002; Roman et al., 2008; World Health Organization, 2011). We find that the response of ozone and $PM_{2.5}$ concentrations to the evolution of the AMO from cold to warm phase may increase the annual excess mortality rate by as much as ~3,300 (95% confidence interval, 1,198–6,037) in the eastern United States (Figure S16) under current emission level and assuming the present-day air quality-meteorology relationship is unchanged.

5. Discussions and Conclusion

Tree-ring data and other climate proxies supply evidence that the AMO extends at least five centuries back in time (Gray et al., 2004; Mann et al., 2009), suggesting that this multidecadal variability is likely to continue in the future, with implications for air quality planning. However, when averaged across an ensemble of climate models, this multidecadal variability becomes tiny in future projections over the 2000–2100 time frame (Figure S17a). This can be explained by the large spread in both the magnitude and frequency of the AMO in CMIP5 models (L. Zhang & Wang, 2013). As inferred from an ensemble of 33 CMIP5 models, average summertime temperature over the eastern United States increases by +1.36 K under Representative Concentration Pathway (RCP) 4.5 scenario from 2015 to 2050, or about double the +0.74 K change of temperature in a half-AMO cycle (~35 years; Figure S17b). Barring any change in its observed periodicity of 50–90 years, the AMO is likely to shift into a cold phase over the next few decades (Enfield & Cid-Serrano, 2010; Keenlyside et al., 2008). This shift may offset up to 50% of the climate penalty on air quality in the eastern United States brought on by global warming in coming decades, as inferred from Figure S17b. This also implies that previous projections of air quality in the future climate may be biased if the AMO effects are not considered.

In conclusion, our results show that the Atlantic Multidecadal Oscillation (AMO) is a major driver of multidecadal variability of summertime surface air quality over the eastern United States, resulting from large-scale ocean-atmosphere interactions. In one-half cycle (~35 years) of the AMO from cold to warm phase with constant anthropogenic emissions, summertime MDA8 ozone concentrations increase by 1–3 ppbv in the northeast and 2–5 ppbv in the Great Plains; summertime $PM_{2.5}$ concentrations increase by 0.6–1.0 $\mu g\ m^{-3}$ in the northeast and southeast. Such a shift occurred from 1940 to 1970 could occur again in the mid-21st century. The resulting impact on mortality rates could be an increase of ~3,300 excess deaths per year in one-half cycle of AMO (methods in Text S2). Although the drivers of AMO are not well known (Booth et al., 2012; Enfield & Cid-Serrano, 2010; Kumar et al., 2013; Kunkel et al., 2006; R. Zhang et al., 2013) and the capability of free-running climate models to capture the AMO is limited (Yang et al., 2013), the long-term air quality planning in coming decades would benefit from consideration of a potentially large AMO influence.

Acknowledgments

This work was supported by the National Institute of Environmental Health Sciences (R21ES022585), and the U.S. Environmental Protection Agency (USEPA RD-83587201). The contents of this publication are solely the responsibility of the grantee and do not necessarily represent the official views of the USEPA. All data used in this study are publically accessible. All data used in this study can be accessed via doi:10.7910/DVN/JERMCE.

References

Allan, R., & Ansell, T. (2006). A new globally complete monthly historical gridded mean sea level pressure dataset (HadSLP2): 1850–2004. *Journal of Climate*, *19*(22), 5816–5842. https://doi.org/10.1175/JCLI3937.1

Anderson, G. B., & Bell, M. L. (2011). Heat waves in the United States: Mortality risk during heat waves and effect modification by heat wave characteristics in 43 US communities. *Environmental Health Perspectives*, *119*(2), 210–218. https://doi.org/10.1289/ehp.1002313

Anenberg, S. C., Schwartz, J., Shindell, D., Amann, M., Faluvegi, G., Klimont, Z., … Ramanathan, V. (2012). Global air quality and health co-benefits of mitigating near-term climate change through methane and black carbon emission controls. *Environmental Health Perspectives*, *120*(6), 831–839. https://doi.org/10.1289/ehp.1104301

Barnes, E. A., Fiore, A. M., & Horowitz, L. W. (2016). Detection of trends in surface ozone in the presence of climate variability. *Journal of Geophysical Research: Atmospheres*, *121*, 6112–6129. https://doi.org/10.1002/2015JD024397

Bloomer, B. J., Stehr, J. W., Piety, C. A., Salawitch, R. J., & Dickerson, R. R. (2009). Observed relationships of ozone air pollutionwith temperature and emissions. *Geophysical Research Letters*, *36*, L09803. https://doi.org/10.1029/2009GL037308

Booth, B. B. B., Dunstone, N. J., Halloran, P. R., Andrews, T., & Bellouin, N. (2012). Aerosols implicated as a prime driver of twentieth-century North Atlantic climate variability. *Nature*, *484*(7393), 228–232. https://doi.org/10.1038/nature10946

Cleveland, W. S. (1981). LOWESS: A program for smoothing scatterplots by robust locally weighted regression. *The American Statistician*, *35*(1), 54–54. https://doi.org/10.2307/2683591

Coles, S. G. (2001). *An introduction to statistical modeling of extreme values*. New York: Springer. https://doi.org/10.1007/978-1-4471-3675-0

Compo, G. P., Whitaker, J. S., Sardeshmukh, P. D., Matsui, N., Allan, R. J., Yin, X., … Worley, S. J. (2011). The twentieth century reanalysis project. *Quarterly Journal of the Royal Meteorological Society*, *137*(654), 1–28. https://doi.org/10.1002/qj.776

Cooper, O. R., Gao, R.-S., Tarasick, D., Leblanc, T., & Sweeney, C. (2012). Long-term ozone trends at rural ozonemonitoring sites across the United States, 1990–2010. *Journal of Geophysical Research*, *117*, D22307. https://doi.org/10.1029/2012JD018261

Doherty, R. M., Wild, O., Shindell, D. T., Zeng, G., MacKenzie, I. A., Collins, W. J., … Keating, T. J. (2013). Impacts of climate change on surface ozone and intercontinental ozone pollution: A multi-model study. *Journal of Geophysical Research: Atmospheres*, *118*, 3744–3763. https://doi.org/10.1002/jgrd.50266

Enfield, D. B., & Cid-Serrano, L. (2010). Secular and multidecadal warmings in the North Atlantic and their relationships with major hurricane activity. *International Journal of Climatology*, *30*(2), 174–184.

Fiore, A. M., Dentener, F. J., Wild, O., Cuvelier, C., Schultz, M. G., Hess, P., … Zuber, A. (2009). Multimodel estimates of intercontinental source-receptor relationships for ozone pollution. *Journal of Geophysical Research*, *114*, D04301. https://doi.org/10.1029/2008JD010816

Fiore, A. M., Naik, V., & Leibensperger, E. M. (2015). Air quality and climate connections. *Journal of the Air & Waste Management Association*, *65*(6), 645–685. https://doi.org/10.1080/10962247.2015.1040526

Garcia-Menendez, F., Monier, E., & Selin, N. E. (2017). The role of natural variability in projections of climate change impacts on U.S. ozone pollution. *Geophysical Research Letters*, *44*, 2911–2921. https://doi.org/10.1002/2016GL071565

Gray, S. T., Graumlich, L. J., Betancourt, J. L., & Pederson, G. T. (2004). A tree-ring based reconstruction of the Atlantic Multidecadal Oscillation since 1567 A.D. *Geophysical Research Letters*, *31*, L12205. https://doi.org/10.1029/2004GL019932

Hersbach, H., Peubey, C., Simmons, A., Berrisford, P., Poli, P., & Dee, D. (2015). ERA-20CM: A twentieth-century atmospheric model ensemble. *Quarterly Journal of the Royal Meteorological Society*, *141*(691), 2350–2375. https://doi.org/10.1002/qj.2528

Hodson, D. L. R., Sutton, R. T., Cassou, C., Keenlyside, N., Okumura, Y., & Zhou, T. J. (2010). Climate impacts of recent multidecadal changes in Atlantic Ocean sea surface temperature: A multimodel comparison. *Climate Dynamics*, *34*(7-8), 1041–1058. https://doi.org/10.1007/s00382-009-0571-2

Horton, D. E., & Diffenbaugh, N. S. (2012). Response of air stagnation frequency to anthropogenically enhanced radiative forcing. *Environmental Research Letters*, *7*(4), 044034. https://doi.org/10.1088/1748-9326/7/4/044034

Hu, X., Waller, L. A., Lyapustin, A., Wang, Y., & Liu, Y. (2014). 10-year spatial and temporal trends of $PM_{2.5}$ concentrations in the southeastern US estimated using high-resolution satellite data. *Atmospheric Chemistry and Physics*, *14*(12), 6301–6314. https://doi.org/10.5194/acp-14-6301-2014

Jacob, D. J., & Winner, D. A. (2009). Effect of climate change on air quality. *Atmospheric Environment*, *43*(1), 51–63. https://doi.org/10.1016/j.atmosenv.2008.09.051

Jerrett, M., Burnett, R. T., Pope, C. A. III, Ito, K., Thurston, G., Krewski, D., … Thun, M. (2009). Long-term ozone exposure and mortality. *The New England Journal of Medicine*, *360*(11), 1085–1095. https://doi.org/10.1056/NEJMoa0803894

Jones, P. D., Lister, D. H., Osborn, T. J., Harpham, C., Salmon, M., & Morice, C. P. (2012). Hemispheric and large-scale land-surface air temperature variations: An extensive revision and an update to 2010. *Journal of Geophysical Research*, *117*, D05127. https://doi.org/10.1029/2011JD017139

Kalnay, E., Kanamitsu, M., Kistler, R., Collins, W., Deaven, D., Gandin, L., … Joseph, D. (1996). The NCEP/NCAR 40-year reanalysis project. *Bulletin of the American Meteorological Society*, *77*(3), 437–471. https://doi.org/10.1175/1520-0477(1996)077%3C0437:TNYRP%3E2.0.CO;2

Keenlyside, N. S., Latif, M., Jungclaus, J., Kornblueh, L., & Roeckner, E. (2008). Advancing decadal-scale climate prediction in the North Atlantic sector. *Nature*, *453*(7191), 84–88. https://doi.org/10.1038/nature06921

Kennedy, J. J., Rayner, N. A., Smith, R. O., Saunby, M., & Parker, D. E. (2011). Reassessing biases and other uncertainties in sea-surface temperature observations measured in situ since 1850: 1. Measurement and sampling errors. *Journal of Geophysical Research*, *116*, D14103. https://doi.org/10.1029/2010JD015218

Kumar, S., Kinter, J., Dirmeyer, P. A., Pan, Z., & Adams, J. (2013). Multidecadal climate variability and the “warming hole” in North America: Results from CMIP5 twentieth- and twenty-first-century climate simulations. *Journal of Climate*, *26*(11), 3511–3527. https://doi.org/10.1175/JCLI-D-12-00535.1

Kunkel, K. E., Liang, X. Z., Zhu, J. H., & Lin, Y. R. (2006). Can CGCMs simulate the twentieth-century “warming hole” in the central United States? *Journal of Climate*, *19*(17), 4137–4153. https://doi.org/10.1175/JCLI3848.1

Leibensperger, E. M., Mickley, L. J., & Jacob, D. J. (2008). Sensitivity of U.S. air quality to midlatitude cyclone frequency and implications of 1980–2006 climate change. *Atmospheric Chemistry and Physics*, *8*(23), 7075–7086. https://doi.org/10.5194/acp-8-7075-2008

Lelieveld, J., Evans, J. S., Fnais, M., Giannadaki, D., & Pozzer, A. (2015). The contribution of outdoor air pollution sources to premature mortality on a global scale. *Nature*, *525*(7569), 367–371. https://doi.org/10.1038/nature15371

Mann, M. E., Zhang, Z., Rutherford, S., Bradley, R. S., Hughes, M. K., Shindell, D., … Ni, F. (2009). Global signatures and dynamical origins of the Little Ice Age and Medieval climate anomaly. *Science*, *326*(5957), 1256–1260. https://doi.org/10.1126/science.1177303

McCabe, G. J., Palecki, M. A., & Betancourt, J. L. (2004). Pacific and Atlantic Ocean influences on multidecadal drought frequency in the United States. *Proceedings of the National Academy of Sciences of the United States of America*, *101*(12), 4136–4141. https://doi.org/10.1073/pnas.0306738101

McKinnon, K. A., Rhines, A., Tingley, M. P., & Huybers, P. (2016). Long-lead predictions of eastern United States hot days from Pacific sea surface temperatures. *Nature Geoscience*, *9*(5), 389–394. https://doi.org/10.1038/ngeo2687

Nigam, S., Guan, B., & Ruiz-Barradas, A. (2011). Key role of the Atlantic Multidecadal Oscillation in 20th century drought and wet periods over the Great Plains. *Geophysical Research Letters*, *38*, L16713. https://doi.org/10.1029/2011GL048650

Pappin, A. J., Mesbah, S. M., Hakami, A., & Schott, S. (2015). Diminishing returns or compounding benefits of air pollution control? The case of NO_x and ozone. *Environmental Science & Technology*, *49*(16), 9548–9556. https://doi.org/10.1021/acs.est.5b00950

Pope, C. A. III, Burnett, R. T., Thun, M. J., Calle, E. E., Krewski, D., Ito, K., & Thurston, G. D. (2002). Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. *Journal of the American Medical Association*, *287*(9), 1132–1141. https://doi.org/10.1001/jama.287.9.1132

Rayner, N. A., Parker, D. E., Horton, E. B., Folland, C. K., Alexander, L. V., Rowell, D. P., … Kaplan, A. (2003). Global analyses of sea surface temperature, sea ice, and night marine air temperature since the late nineteenth century. *Journal of Geophysical Research*, *108*(D14), 4407. https://doi.org/10.1029/2002JD002670

Roman, H. A., Walker, K. D., Walsh, T. L., Conner, L., Richmond, H. M., Hubbell, B. J., & Kinney, P. L. (2008). Expert judgment assessment of the mortality impact of changes in ambient fine particulate matter in the US. *Environmental Science & Technology*, *42*(7), 2268–2274. https://doi.org/10.1021/es0713882

Schmidt, G. A., Kelley, M., Nazarenko, L., Ruedy, R., Russell, G. L., Aleinov, I., … Zhang, J. (2014). Configuration and assessment of the GISS ModelE2 contributions to the CMIP5 archive. *Journal of Advances in Modeling Earth Systems*, *6*(1), 141–184. https://doi.org/10.1002/2013MS000265

Schneider, U., Becker, A., Finger, P., Meyer-Christoffer, A., Rudolf, B., & Ziese, M. (2011). GPCC full data reanalysis version 6.0 at 0.5°: Monthly land-surface precipitation from rain-gauges built on GTS-based and historic data. https://doi.org/10.5676/DWD_GPCC/FD_M_V7_050

Shen, L., & Mickley, L. J. (2017). Influence of large-scale climate patterns on summertime U.S. ozone: A seasonal predictive model for air quality management. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(10), 2491–2496. https://doi.org/10.1073/pnas.1610708114

Shen, L., Mickley, L. J., & Gilleland, E. (2016). Impact of increasing heat waves on U.S. ozone episodes in the 2050s: Results from a multimodel analysis using extreme value theory. *Geophysical Research Letters*, *43*, 4017–4025. https://doi.org/10.1002/2016GL068432

Shen, L., Mickley, L. J., & Murray, L. (2017). Influence of 2000–2050 climate change on particulate matter in the United States: Results from a new statistical model. *Atmospheric Chemistry and Physics*, *17*(6), 4355–4367. https://doi.org/10.5194/acp-17-4355-2017

Shen, L., Mickley, L. J., & Tai, A. P. K. (2015). Influence of synoptic patterns on surface ozone variability over the eastern United States from 1980 to 2012. *Atmospheric Chemistry and Physics*, *15*(19), 10925–10938. https://doi.org/10.5194/acp-15-10925-2015

Shindell, D. T., Lee, Y., & Faluvegi, G. (2016). Climate and health impacts of US emissions reductions consistent with 2 °C. *Nature Climate Change*, *6*(5), 503–507. https://doi.org/10.1038/nclimate2935

Smith, T. M., Reynolds, R., Peterson, T. C., & Lawrimore, J. (2008). Improvements to NOAA's historical merged land-ocean surface temperature analysis (1880–2006). *Journal of Climate*, *21*(10), 2283–2296. https://doi.org/10.1175/2007JCLI2100.1

Sutton, R. T., & Hodson, D. L. (2007). Climate response to basin-scale warming and cooling of the North Atlantic Ocean. *Journal of Climate*, *20*(5), 891–907. https://doi.org/10.1175/JCLI4038.1

Sutton, R. T., & Hodson, D. L. R. (2005). Atlantic Ocean forcing of North American and European summer climate. *Science*, *309*(5731), 115–118. https://doi.org/10.1126/science.1109496

Tai, A., Mickley, L., Jacob, D., Leibensperger, E., Zhang, L., Fisher, J., & Pye, H. (2012). Meteorological modes of variability for fine particulate matter ($PM_{2.5}$) air quality in the United States: Implications for $PM_{2.5}$ sensitivity to climate change. *Atmospheric Chemistry and Physics*, *12*(6), 3131–3145. https://doi.org/10.5194/acp-12-3131-2012

Trenberth, K. E., & Shea, D. J. (2006). Atlantic hurricanes and natural variability in 2005. *Geophysical Research Letters*, *33*, L12704. https://doi.org/10.1029/2006GL026894

Van Oldenborgh, G. J., Raa, L. T., Dijkstra, H. A., & Philip, S. Y. (2009). Frequency-dependent effects of the Atlantic meridional overturning on the tropical Pacific Ocean. *Ocean Science*, *5*(3), 293–301. https://doi.org/10.5194/os-5-293-2009

Vose, R. S., Applequist, S., Squires, M., Durre, I., Menne, M. J., Williams, C. N., … Arndt, D. (2014). Improved historical temperature and precipitation time series for U.S. climate divisions. *Journal of Applied Meteorology and Climatology*, *53*(5), 1232–1251. https://doi.org/10.1175/JAMC-D-13-0248.1

Vose, R. S., Arndt, D., Banzon, V. F., Easterling, D. R., Gleason, B., Huang, B., … Wuertz, D. B. (2012). NOAA's merged land-ocean surface temperature analysis. *Bulletin of the American Meteorological Society*, *93*(11), 1677–1685. https://doi.org/10.1175/BAMS-D-11-00241.1

Willmott, C. J., Matsuura, K., & Legates, D. R. (2001). Terrestrial air temperature and precipitation: Monthly and annual time series (1950–1999), Center for climate research version, 1.

World Health Organization (2011). Death estimates for 2008 by cause for WHO member states. WHO Department of Health Statistics.

Yang, X., Rosati, A., Zhang, S., Delworth, T. L., Gudgel, R. G., Zhang, R., … Zeng, F. (2013). A predictable AMO-like pattern in the GFDL fully coupled ensemble initialization and decadal forecasting system. *Journal of Climate*, *26*(2), 650–661. https://doi.org/10.1175/JCLI-D-12-00231.1

Zhang, L., & Wang, C. (2013). Multidecadal North Atlantic sea surface temperature and Atlantic meridional overturning circulation variability in CMIP5 historical simulations. *Journal of Geophysical Research: Oceans*, *118*, 5772–5791. https://doi.org/10.1002/jgrc.20390

Zhang, R., Delworth, T. L., Sutton, R., Hodson, D. L. R., Dixon, K. W., Held, I. M., … Vecchi, G. A. (2013). Have aerosols caused the observed Atlantic multidecadal variability? *Journal of the Atmospheric Sciences*, *70*(4), 1135–1144. https://doi.org/10.1175/JAS-D-12-0331.1