AGU PUBLICATIONS

Geophysical Research Letters

RESEARCH LETTER
10.1002/2014GL060184

Key Points:
- Arctic temperature variability cannot be reproduced without the AMO
- Anthropogenic component can be isolated
- Rate of recent Arctic anthropogenic warming is ~0.31K/decade

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Citation:
Chylek, P., N. Hengartner, G. Lesins, J. D. Klett, O. Humlum, M. Wyatt, and M. K. Dubey (2014), Isolating the anthropogenic component of Arctic warming, *Geophys. Res. Lett.*, *41*, 3569–3576, doi:10.1002/2014GL060184.

Received 9 APR 2014
Accepted 27 APR 2014
Accepted article online 2 MAY 2014
Published online 28 MAY 2014

Isolating the anthropogenic component of Arctic warming

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Abstract Structural equation modeling is used in statistical applications as both confirmatory and exploratory modeling to test models and to suggest the most plausible explanation for a relationship between the independent and the dependent variables. Although structural analysis cannot prove causation, it can suggest the most plausible set of factors that influence the observed variable. We apply structural model analysis to the annual mean Arctic surface air temperature from 1900 to 2012 to find the most effective set of predictors and to isolate the anthropogenic component of the recent Arctic warming by subtracting the effects of natural forcing and variability from the observed temperature. We find that anthropogenic greenhouse gases and aerosols radiative forcing and the Atlantic Multidecadal Oscillation internal mode dominate Arctic temperature variability. Our structural model analysis of observational data suggests that about half of the recent Arctic warming of 0.64 K/decade may have anthropogenic causes.

1. Introduction

The influence of the Atlantic Ocean on the Arctic as well as on global climate has been long recognized. One of the signatures of the current multidecadal warming period is that the Arctic has been warming at a faster pace than the global average. Although this Arctic amplification has been discussed for some time, its origin is not yet fully understood [*Chylek et al.*, 2009; *Holland and Bitz*, 2003; *Serreze and Francis*, 2006; *Serreze et al.*, 2009; *Screen and Simmonds*, 2010; *Lesins et al.*, 2012; *Taylor et al.*, 2013; *Pithan and Mauritsen*, 2014; *Zhang et al.*, 2007]. In spite of a significant progress in model development, the interplay between radiative forcing due to the increasing concentration of greenhouse gases and the dynamical variability of the complex atmosphere-ocean system remains unresolved. The Intergovernmental Panel on Climate Change Fifth Assessment Report (IPCC AR5) of 2013 lists natural climate variability as one of the possible causes responsible for the recent slower rate of warming than predicted by climate models. A significant multidecadal scale natural variability signal may be superimposed upon the warming due to greenhouse gases [*DeSol et al.*, 2011; *Wallace et al.*, 2012; *North*, 2012] that could dampen or amplify the latter. The separation of anthropogenic changes and natural climate variability in the observed record remains a challenging problem that is critical to model projections of impacts in the 21st century. In this report we use regression analysis (structural equation modeling) to isolate the anthropogenic component in the recent Arctic warming using available observations.

A multiple linear regression analysis has been applied recently to global [*Lean and Rind*, 2008; *Foster and Rahmstorf*, 2011; *Zhou and Tung*, 2013; *Canty et al.*, 2013; *Chylek et al.*, 2013, 2014] as well as to regional climate data sets. The set of explanatory variables used included radiative forcing by anthropogenic greenhouse gases (GHG), anthropogenic aerosols (AER), solar variability (SOL), volcanic aerosols (VOLC), and oceanic influences characterized by the El Niño–Southern Oscillation (ENSO) and the Atlantic Multidecadal Oscillation (AMO). In the following, we use regression and structural model analysis to estimate the anthropogenic component of the recent (post 1975) Arctic warming.

2. Data Sets

We use NASA Goddard Institute for Space Studies (GISS) Surface Temperature (GISTEMP) temperature time series derived from observations at meteorological stations (land only) for the region north of 64°N (http://data.giss.nasa.

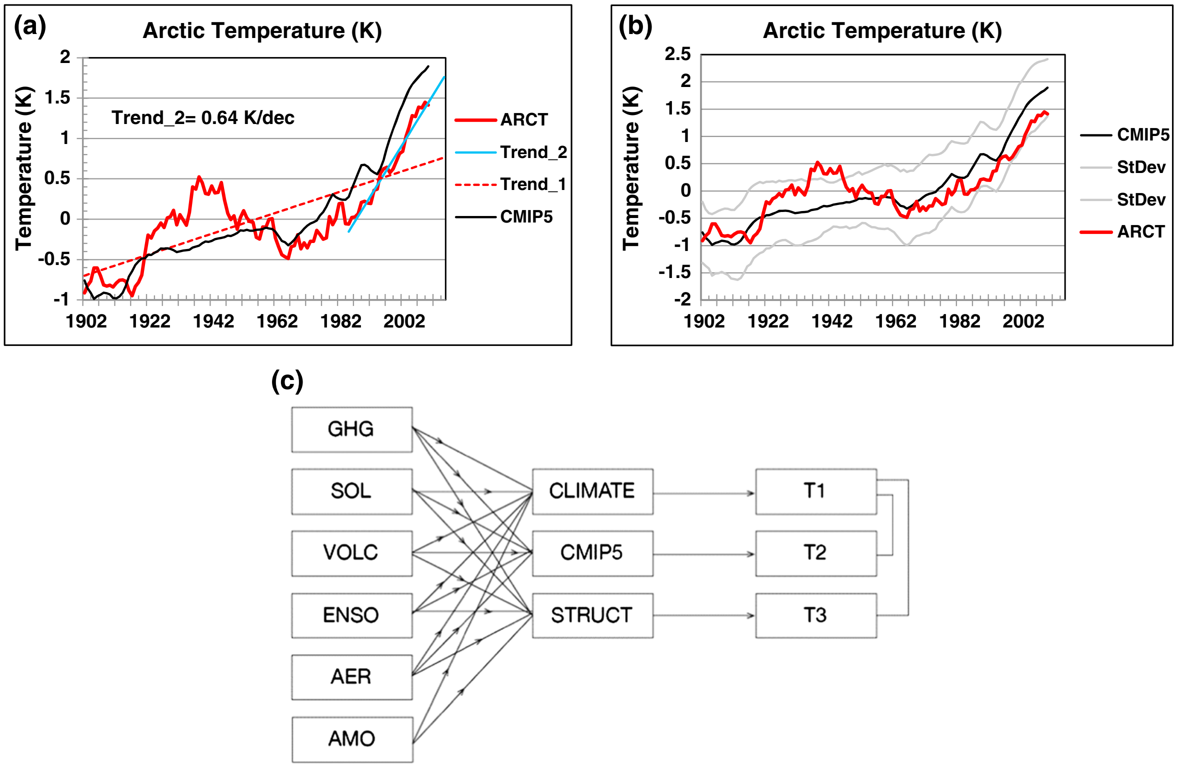

Figure 1. (a) The Arctic temperature anomaly (after NASA GISTEMP data as described in the text) and temperature trends in indicated time intervals. For comparison the ensemble mean of all 108 simulations by the CMIP5 models (ACCESS1-0, ACCESS1-3, bcc-csm1-1, bcc-csm1-1-m, BNU-ESM, CanESM2, CCSM4, CESM1-BGC, CESM1-CAM5, CMCC-CM, CMCC-CMS, CNRM-CM5, CSIRO-Mk3-6-0, EC-EARTH, FGOALS-g2, FIO-ESM, GFDL-CM3, GFDL-ESM2G, GFDL-ESM2M, GISS-E2-H, GISS-E2-H, GISS-E2-H, GISS-E2-H-CC, GISS-E2-R, GISS-E2-R, GISS-E2-R, GISS-E2-R-CC, HadGEM2-AO, HadGEM2-CC, HadGEM2-ES, inmcm4, IPSL-CM5A-LR, IPSL-CM5A-MR, IPSL-CM5B-LR, MIROC5, MIROC-ESM, MIROC-ESM-CHEM, MPI-ESM-LR, MPI-ESM-MR, MRI-CGCM3, NorESM1-M, and NorESM1-ME) of the historic twentieth century climate and the RCP4.5 path is also shown. The temperature anomalies are with respect to 1900–2010 average. (b) CMIP5 ensemble mean and 1 standard deviation of model simulations (gray). The CMIP5 ensemble mean accounts for 76.2% of the observed Arctic temperature variance (1900–2012). (c) Considered structural model for the Arctic temperature. Square boxes represent explanatory variables which serve as input into the structural model (STRUCT), CMIP5 models, and real climate to produce the observed temperature T1 and modeled temperatures T2 and T3. The structural model-simulated temperature T3 is then compared to the observed temperature T1, and the R^2_{adj} is used as a metrics to evaluate efficiency of the model.

gov/gistemp/ for our analysis). We selected the land data only to eliminate any overlap between regions used to compute the AMO index (North Atlantic) and the mean Arctic temperatures (north of 64°N). In the GISS data, Arctic regions without meteorological stations and temperature data are filled in by extrapolation from stations up to 1200 km away [*Hansen et al.*, 2007, 2011]. This procedure reduces the potential underestimation of recent Arctic warming that may occur in some other data sets [*Cowtan and Way*, 2013].

The observed Arctic temperature (Figure 1a) shows the early twentieth century warming period followed by a significant midcentury cooling (from 1940 to 1965) and the current warming with the 1985–2012 warming trend of 0.64 K/decade. The ensemble mean of 108 individual simulations by all the Coupled Model Intercomparison Project Phase 5 (CMIP5) models (simulation of the 1900–2005 climate complemented by the 2006–2012 representative concentration pathways 4.5 (RCP4.5) projection) fails to reproduce the 1940s peak in Arctic temperature in spite of a wide range of individual simulations (Figure 1b).

The radiative forcing time series by GHG, AER1, SOL, and VOLC (Figure 2) are from *Hansen et al.* [2007, 2011], including updates as described on the NASA GISS website (http://data.giss.nasa.gov/modelforce/Fe.1880-2011.txt). The ENSO 3.4 index (170°W to 120°W and 5°N to 5°S) is from http://www.esrl.noaa.gov/psd/gcos_wgsp/Timeseries/Data/nino34.long.data. We consider three different methods of deriving the AMO index (Figure 2): the first is a smoothed NOAA long series [*Kaplan et al.*, 1998] provided by the NOAA/OAR (Oceanic and Atmospheric Research)/Earth System Research Laboratory Physical Sciences Division, Boulder, Colorado, USA, at their website http://www.esrl.noaa.gov/psd/data/timeseries/AMO/. The second is the AMO index after *Trenberth and Shea* [2006], and the third one is the AMO index as defined by *Parker et al.* [2007]. The monthly indices are averaged to

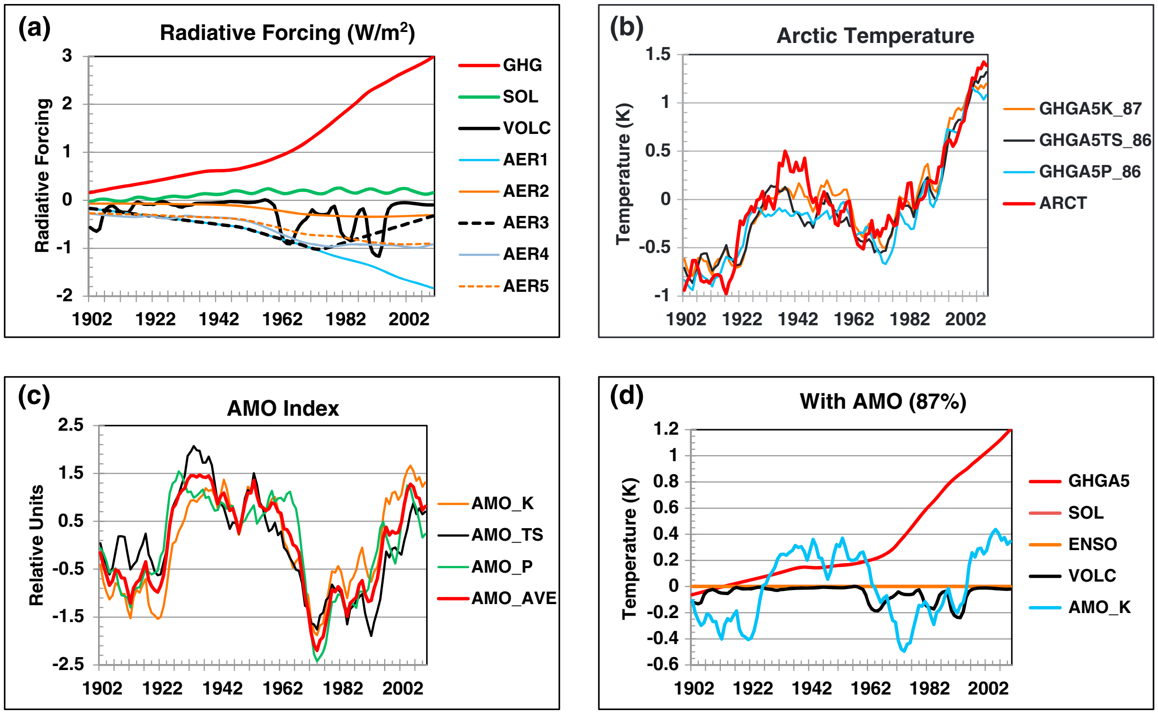

Figure 2. (a) The twentieth century radiative forcing due to anthropogenic greenhouse gases (GHG), solar Variability (SOL), volcanic aerosols (VOLC), and different models of anthropogenic aerosols (AER1 to AER5) described in the text. (b) Observed Arctic temperature variability (red), a regression model of the Arctic temperature with AER5 aerosol forcing, including a direct and an indirect aerosol effect as prescribed by the IPCC AR5, and different AMO index (after Kaplan = K, Trenberth and Shea = TS, and Parker = P). (c) Three forms of the AMO index considered in this study and their average. (d) Distribution of Arctic temperature variability among the predictors. Only GHGA, AMO, and VOLC are statistically significant predictors when AMO is added to the set of explanatory variables.

obtain annual values and then normalized to zero mean and unit variance. All data are smoothed further with a 5 year moving average to remove annual fluctuations and to facilitate the isolation of multidecadal-scale variability.

Since the aerosol radiative forcing is relatively uncertain, in addition to the NASA GISS-prescribed aerosol forcing (AER1), we consider alternate forcings (Figure 2) provided by the IPCC Fifth Assessment Report, namely, a direct aerosol effect only (AER2), a direct plus indirect forcing (AER5), our own hypothetical forcing (AER3) simulating the sulfate aerosol decrease since the 1980s, and the aerosol radiative forcing (AER4) estimated by *Mascioli et al*. [2012].

The radiative forcing due to GHG and AER are highly anticorrelated. The presence of collinearity makes it difficult to separate the effects of the collinear explanatory variables. There are two frequently used solutions to this problem, either drop one of collinear predictors from the set of explanatory variables or combine the two collinear predictors into a single predictor. Since we are interested in the combined effect of anthropogenic activities, we combine the GHG and AER radiative forcings into a single predictor, GHGA, defined as a sum of radiative forcing due to GHG and AER. The same solution has been adopted by *Lean and Rind* [2008] and *Chylek et al*. [2013].

There is also a correlation between the GHG and SOL ($r = 0.60$), which leads to an increased uncertainty of the GHG and SOL regression coefficients. Although the relative uncertainty of the GHG contribution is expected to be small, because of this GHG-SOL collinearity, the regression analysis cannot accurately determine the magnitudes of the solar influence on global or regional temperature variability [*Lean and Rind*, 2008; *Scafetta and West*, 2006].

3. Structural Model Analysis

We use a linear structural model as the basic tool in our analysis. The annual mean Arctic temperature is assumed to have the time-dependent form

$$T(t) = A_o + A_1\,\mathrm{GHGA}(t) + A_2\,\mathrm{SOL}(t) + A_3\mathrm{VOLC}(t) + A_4\,\mathrm{ENSO}(t) + A_5\,\mathrm{AMO} + \varepsilon,$$

where the individual predictors are given by time series described in the preceding section, ε is an error term, and the expansion coefficients are determined by minimizing the sum of squared residuals.

Table 1. Summary of the Structural Models Used and the Fraction of Arctic Temperature Variance Accounted for Within the Years 1900–2012[a]

Case No.	Predictors of the Structural Model	Explained Variance (%)
	Different Aerosols	
1	GHGAs + SOL + VOLC + ENSO	70.2% to 75.9%
2	GHGAs + (SOL) + VOLC + (ENSO) + AMO_K	85.3% to 87.1%
3	GHGAs + VOLC + AMO_K	85.0% to 87.3%
4	GHGAs + AMO_K	84.8% to 86.6%
	Different AMOs	
5	GHGA5 + VOLC + AMOs	85.8% to 87.2%
6	GHGA5 + AMOs	82.2% to 86.5%
	CMIP5 Models	
7	CMIP5 ensemble mean	76.2%

[a]The listed results are for aerosol radiative forcings AER1 to AER5 (Figure 2) and the AMO index according to *Kaplan et al.* [1998] (AMO_K), *Trenberth and Shea* [2006] (AMO_TS), and *Parker et al.* [2007] (AMO_P). Different aerosol radiative forcing and different AMO indices with the three-predictor (GHGA, AMO, and VOLC) models produce only minor changes of the model explanatory power from 85.0% to 87.3%. For comparison the fraction of the Arctic temperature variance accounted for by the CMIP5 ensemble mean (76.2%) is also shown. The results demonstrate the importance of the AMO in structural climate models and the fact that the AMO is not captured by the CMIP5 ensemble mean of simulations. Parentheses indicate statistically insignificant predictors.

Multiple linear regression assumes that the dependent variable (Arctic temperature in our case) can be written as a linear combination of the explanatory variables, with the expansion coefficients determined by minimizing the sum of the squared differences between the observed and the modeled dependent variable. The quality of the model can be evaluated by comparing the square of the multiple correlation coefficients (R^2_{adj}) adjusted for the number of predictors used in a given model [e.g., *Wilks*, 2006].

Our structural model is shown schematically in Figure 1c. The explanatory variables provide input to the model which uses regression to find the optimal weightings for the explanatory variables to produce a model temperature (T3) that best fits the observational temperature (T1). A comparison of the model and observed temperatures thus allows a ranking of the effectiveness of different sets of explanatory variables in reproducing observations. Similarly, the ensemble mean of CMIP5 climate models produces the Arctic temperature T2 which is then compared with the observed temperature.

We begin our search for the best model with a comparison of two models of the Arctic temperature variability. The first model includes GHGA, SOL, VOLC, and ENSO as a set of physically plausible explanatory variables. The second set of predictors is the same but augmented by the AMO. We use the sum of AER and GHG radiative forcing to produce the combined GHGA forcing used in the above regression equation. The task is to determine which model best reconstructs the Arctic mean surface air temperature. We find that the use of alternate aerosol forcings (AER1 to AER5) leads only to minor changes in the regression's explanatory power (Table 1); the adjusted R^2_{adj} varies between 0.702 and 0.759.

The regression model with all radiative forcings and ENSO accounts for 70.2% to 75.9% of the observed Arctic temperature variance for the 1900–2012 period (Table 1). With the AMO index added to the set of explanatory variables, the fraction of the observed temperature variance accounted for increases to 85.3% to 87.1% (Table 1). However, in this case both the SOL and ENSO predictors become statistically insignificant (the AMO acts as a mediator in a structural model analysis). When they are deleted from the set of explanatory variables, we are left with three predictors GHGA, AMO, and VOLC that have essentially unchanged performance accounting for 85.0% to 87.3% of temperature variance (Table 1), depending on the aerosol model and the AMO used. The minimal model (a parsimonious model with a high explanatory power and a minimum set of predictors) that uses just GHGA and the AMO as predictors still accounts for 82.2% to 86.6% of the temperature variance. Adding the AMO to a set of explanatory variables thus leads to a highly statistically significant ($p < 0.01$) improvement. The model with the AMO is clearly superior to one without it. This is in agreement with earlier conclusions [*Zhou and Tung*, 2013; *Chylek et al.*, 2013, 2014; *Canty et al.*, 2013; *Muller et al.*, 2013] that the AMO is an essential explanatory variable in both global and regional (in our case the Arctic) climate analysis.

The preceding analysis employed AER1 to AER5 as the aerosol radiative forcing. Although the forcings differ somewhat (Figure 2a), the results of the regression models with these different aerosol forcings are close to each other (Table 1). In the following, we use AER5 (aerosol radiative forcing including a direct and an indirect aerosol effect according to the IPCC AR5) as representative of the aerosol radiative forcing. A limitation of our aerosol treatment is that it represents the global mean forcing, and so does not account for any local effects due to spatially inhomogeneous aerosol distributions which may affect the forcing in the Arctic [*Shindell and Faluvegi*, 2009; *Flanner*, 2013; *Sand et al*., 2013].

4. The AMO as an Explanatory Variable

The origin of the AMO [*Schlesinger and Ramankutty*, 1994] is not yet fully understood [*Knight et al*., 2005; *Dima and Lohmann*, 2007; *Chylek et al*., 2009; Frankcombe and Dijkstra, 2011; *Gulev et al*., 2013]. Some models simulate the twentieth century AMO-like temperature variability by a strong aerosol effect [*Booth et al*., 2012], which may not be consistent with observations [*Zhang et al*., 2013; *Chylek et al*., 2014]. Extensive research [e.g., *Parker et al*., 2007; *van Oldenborg et al*., 2009; *Mahajan et al*., 2011] suggests that the basic multidecadal AMO cycle is connected to the Atlantic Meridional Overturning Circulation. The AMO has been implicated in regional climate variability [e.g., *Folland et al*., 1984, 1986; *Polyakov and Johnson*, 2000; *Chylek et al*., 2013], and AMO proxy data [*Delworth and Mann*, 2000, *Gray et al*., 2004, *Chylek et al*., 2011, 2012] suggest that the AMO has persisted for many hundreds of years, indicating a high probability that it is a natural mode rather than a recent anthropogenic effect.

The use of the AMO as an explanatory variable in the analysis of the Arctic climate is also supported by the hypothesized "stadium wave" [*Wyatt et al*., 2012; *Wyatt and Curry*, 2013], which propagates the climate signal across the Northern Hemisphere through a network of synchronized ocean, ice, and atmospheric indices. As the stadium wave propagates through the index network, the multidecadal time-varying component of Arctic surface air temperature evolves in close association with the AMO. Sea ice in the West Eurasian Arctic, particularly in the Barents and Kara Seas, is assumed to be the link that connects the AMO to Arctic temperatures. Sea ice extent in this region, where Arctic ice is uniquely exposed to open ocean, is largely governed by the AMO, the positive phase of which governs the inflow of warm, saline water into the West Eurasian shelf seas [*Bengtsson et al*., 2004; *Polyakov et al*., 2004, 2005, 2010]. Sea ice cover regulates ocean heat flux to the atmosphere, the effects of which strongly influence Arctic surface temperature. The AMO and sea ice in the Eurasian Arctic sustain the stadium wave signal propagation, thereby imprinting the decadal-scale variability on the Arctic surface air temperature [*Wyatt and Curry*, 2013]. Additional justification for use of the AMO as an explanatory variable has been presented recently elsewhere [*Zhou and Tung*, 2013; *Canty et al*., 2013; *Chylek et al*., 2013; *Muller et al*., 2013].

On the other hand, since the AMO is related to the mean sea surface temperatures of the North Atlantic, which is a regional time series, its role as an independent explanatory variable may be questioned. However, there is observational evidence that in the midlatitude North Atlantic and on time scales longer than 10 years, surface turbulent heat fluxes are indeed driven by the ocean and force the atmosphere [*Gulev et al*., 2013]. Thus, on the longer times cales of interest in our study (decadal and more), the evidence shows that the energy flow is predominantly from ocean to atmosphere, in support of the use of the AMO as an explanatory variable in regression models. Furthermore, we have used land-only Arctic temperature data in our analysis to minimize the aforementioned cross contamination (confounding in statistics).

We underscore the key result of our analysis that the regression model with just two (GHGA and the AMO) explanatory variables is able to account for up to 86.6% ($R^2_{adj} = 0.866$) of the observed Arctic temperature variance. Neither the AMO nor the GHGA forcings can be excluded from any regression model without a significant loss of accuracy in reconstructing the observed 1900–2012 Arctic temperature variability.

5. Anthropogenic Components of the Arctic Warming

The Arctic temperature variability is dominated by global radiative forcing due to greenhouse gases and aerosols (GHGA) and by the AMO (Figure 2d). The partitioning of the variability among the GHGA and the AMO does not change significantly between the models as long as the two significant predictors (GHGA and AMO) are present.

In order to isolate the anthropogenic components of the Arctic warming, we follow the procedure suggested earlier [*Foster and Rahmstorf*, 2011; *Zhou and Tung*, 2013] of subtracting the effects of all known forcings

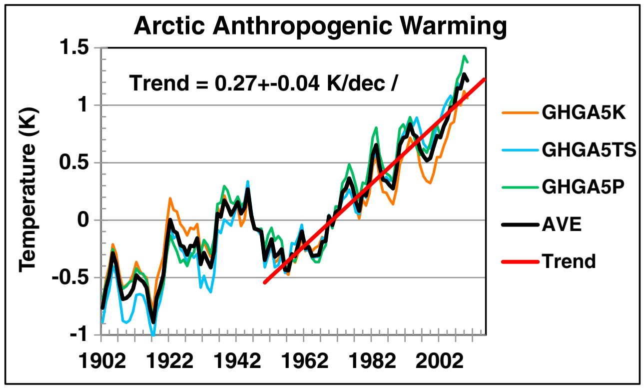

Figure 3. Anthropogenic contribution to Arctic warming using the aerosol radiative forcing (AER5) as prescribed by the IPCC AR5 of 2013 and three versions of the AMO indices (after *Kaplan et al*. [1998] (K), *Trenberth and Shea* [2006] (TS), *Parker et al*. [2007] (P)), and their average (black line). The average post-1955 warming trend is 0.27 K ± 0.04 K/decade (red line).

except the anthropogenic (GHGA) from the observed temperature variability. The result of this procedure depends slightly on how the AMO index is defined. The AMO index provided by NOAA is based on a linearly detrended North Atlantic SST. Instead of a linear detrending, *Trenberth and Shea* [2006] subtract the global mean SST to derive the AMO index, while *Parker et al*. [2007] identified the AMO as the third EOF (empirical orthogonal function) in the worldwide SST. By averaging the anthropogenic warming obtained with these three cases of the AMO index, we find the anthropogenic warming rate from 1955 to 2012 to be 0.27 K ± 0.04 per decade (Figure 3) and 0.31 ± 0.02 from 1985 to 2012. Here 1 standard deviation, taken as the uncertainty, is based on the three different AMO choices. Our results suggest that only about half of the recent (1985–2012) Arctic warming (of 0.64 K/decade) may be due to anthropogenic causes.

6. Summary and Discussion

The addition of the AMO index to the set of commonly used explanatory variables (radiative forcing due to greenhouse gases and anthropogenic aerosol (GHGA), volcanic eruptions (VOLC), solar variability (SOL), and the ENSO index) increases the fraction of Arctic temperature variance (1900–2012) accounted for from 70–76% to 85–87%. This increase is highly statistically significant ($p < 0.01$), which indicates that a model of the Arctic temperature which includes the AMO is significantly better than a model without it. For comparison, the CMIP5 ensemble mean (Figure 1) accounts for 76% of the Arctic temperature variance.

In our analysis, we use the Arctic temperature data (north of 64°N) from the NASA GISS. Data from the early part of the twentieth century have a large uncertainty due to the small number of meteorological stations operating during that time. To show how our results may be affected by this uncertainty, we have repeated our analysis using a temperature data set starting in 1930 (instead of 1900 in our full analysis) when the number of stations had significantly increased. Using this shorter time series, we find the 1985–2012 trend of the anthropogenic Arctic warming to be 0.32 K/decade, compared to 0.31 K/decade found earlier. Thus, the uncertainty of the early data does not affect our model suggestion that only about half of the observed recent Arctic warming (0.64 K/decade) can be attributed to anthropogenic influences.

The anthropogenic component of the Arctic warming was estimated by subtracting the natural variability (solar variability, volcanic eruptions, ENSO, and AMO) from the observed Arctic temperature [*Foster and Rahmstorf*, 2011; *Zhou and Tung*, 2013]. We find the recent (1985–2012) rate of anthropogenic Arctic warming to be 0.31 K ± 0.02 K per decade. Since the Arctic has warmed in recent decades at the rate of about 0.64 K/decade, our results suggest that about half of the observed recent Arctic warming trend could be attributed to anthropogenic causes.

The regression analysis and structural modeling is based on correlations between the explanatory and the dependent variables. It uses long-term observables that reflect known and unknown processes in our coupled climate system as well as the driving forces, both anthropogenic and natural. Such empirical analysis can suggest feasible causal links, but it cannot prove causation that will require process-based climate modeling studies. Although an effort has been made to expand structural modeling to include causation [*Pearl*, 2000, 2003], the process has not yet been generally accepted and used.

While the model we use is based on statistical correlations, it accounts for 87% of the observed Arctic temperature variance (considerably higher than the 76% accounted for by the ensemble mean of CMIP5 model simulations). The AMO provides a reasonable first-order estimate of the influence of the large-scale oceanic circulation on decadal and multidecadal time scales. Ultimately, a first-principle model based on relevant physical processes will be necessary for a more definitive account of the Arctic temperature history. In the meantime, a statistical approach such as that presented here can help guide the selection of important processes not yet captured by existing climate models.

Acknowledgments
Reported research (LA-UR-14-22377) was supported in part by the Los Alamos National Laboratory Institute of Geophysics, Planetary Physics, and Signatures. The authors thank Chris Folland and G.L. van Oldenborg for providing updated AMO indices and two anonymous reviewers and the Editor for helping us improve the original manuscript.

The Editor thanks two anonymous reviewers for their assistance in evaluating this paper.

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