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Key Points:

- The anthropogenic emissions most likely determined the nonlinear, secular trend of Arctic warming during the past century
- State-of-the-art climate models overestimate the secular Arctic warming rate since the mid-twentieth century
- Aggravating secular warming rate with time may lead to over-projection of the future Arctic warming

Supporting Information:

- Supporting Information S1

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The Amplified Arctic Warming in the Recent Decades may Have Been Overestimated by CMIP5 Models

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Abstract Realistically representing the Arctic amplification in global climate models (GCMs) represents a key to accurately predict the climate system's response to increasing anthropogenic forcings. We examined the amplified Arctic warming over the past century simulated by 36 state-of-the-art GCMs against observation. We found a clear difference between the simulations and the observation in terms of the evolution of the secular warming rates. The observed rates of the secular Arctic warming increase from 0.14 °C/10a in the early 1890s to 0.21 °C/10a in the mid-2010s, while the GCMs show a negligible trend to 0.35 °C/10a at the corresponding times. The overestimation of the secular warming rate in the GCMs starts from the mid-twentieth century and aggravates with time. Further analysis indicates that the overestimation mainly comes from the exaggerated heating contribution from the Arctic sea ice melting. This result implies that the future secular Arctic warming may have been over-projected.

1. Introduction

The Arctic has experienced a rapid warming during the past decades (Huang et al., 2017). Along with such fast-increasing near surface air temperature (SAT), the Arctic climate has undergone tremendous changes, such as Arctic wetting, reduction of Arctic sea ice thickness and coverage, decrease of snow cover extent and duration, melting of Greenland ice sheet and thawing of permafrost (Box et al., 2019; Chadburn et al., 2017; IPCC, 2013; van den Broeke et al., 2016). These changes also have thrown impacts on the local ecosystem and the climate outside of the Arctic (Greene et al., 2008; Mori et al., 2019). For example, many studies indicated that the loss of Arctic sea ice may lead to more frequent occurrence of extreme weather and climate at boreal mid-latitudes (Chen et al., 2016; Cohen et al., 2014; Mori et al., 2019; Screen et al., 2018).

The warming rate of the Arctic has been found to be more than twice as fast as the global average, which is usually called as Arctic amplification (Chylek et al., 2009; Screen & Simmonds, 2010). As one of the most significant and well-established global warming signatures, the Arctic amplification has gotten a lot of attention (Acosta Navarro et al., 2016; Cohen et al., 2014; Serreze & Barry, 2011). The feedback effects associated with temperature, surface albedo, as well as water vapor and clouds have been suggested for the amplified Arctic warming (Dai et al., 2019; Gao et al., 2019; Pithan & Mauritsen, 2014; Praetorius et al., 2018). While a number of local and remote positive feedbacks contributed to the Arctic warming (Jeong et al., 2014; Screen et al., 2012; Winton, 2006), sea ice change has been identified as one of the key players in the amplification (Dai et al., 2019; Screen & Simmonds, 2010). Given the importance of diminishing sea ice over the Arctic to global climate system, especially the great concern of its impact on middle latitude extreme weather and climate (Mori et al., 2019; Zhang et al., 2018), reliable future projections of climate change rely on the realistic representation of the Arctic amplification in climate models.

The Arctic warming over the past century has been attributed to anthropogenic influence (Gillett et al., 2008; Najafi et al., 2015). With the increase of the human emissions, anthropogenic influence will continue playing a leading role in the future Arctic climate. Therefore, quantitatively examining the contribution of human influence in the past Arctic warming will increase our understanding of the representation of the amplified Arctic warming in climate models and improve our predictions of future climate change.

In the past, a linear trend analysis method was widely used to calculate the warming (e.g., Fyfe, von Salzen, et al., 2013; IPCC, 2013). In reality, however, the rate of human emissions is time dependent and the climate

system has significant internal variability on various temporal scales (IPCC, 2013). Thus, the response of SAT to anthropogenic forcings should be varying with time (Duan et al., 2019; Ji et al., 2014; Wu et al., 2007). As the linear trend could not appropriately represent such nonlinear response of SAT to anthropogenic forcings, a method called ensemble empirical mode decomposition (EEMD) was suggested for such nonlinear analysis (Wu & Huang, 2009). In this study, we focus on the secular Arctic warming associated with human influence with the method of EEMD by comparing an observational data set and simulations from 36 Coupled Model Intercomparison Project Phase 5 (CMIP5) GCMs (Taylor et al., 2012).

The remainder of this manuscript is organized as follows: section 2 introduces the data and method. The results are presented in section 3. In section 4, we give the conclusion and discussion.

2. Data and Method

In this work, the Arctic is defined as a geographic domain poleward of 60°N, and our research focuses on the annual Arctic SAT, which is calculated from December of a year to the following November. Considering detectable anthropogenic influence on the northern middle-high latitudes since the late nineteenth century (Duan et al., 2019) and inclusion of the latest change of the Arctic SAT, such as record-breaking Arctic warming during the past several years (Richter-Menge et al., 2017), 1880–2017 is chosen here as the study period. The observational data set HadCRUT4.6 (hereafter, HadCRUT) is used in this study, which is an updated observed monthly global temperature anomaly on a 5° grid relative to the reference period 1961–1990. HadCRUT is composed of direct observations from land component CRUTEM4 and marine component HadSST3. The CRUTEM4 is the observed land surface air temperature data set provided by the Climatic Research Unit at the University of East Anglia, while the HadSST3 is the observed sea surface temperature (SST) data set from the Met Office Hadley Centre (Morice et al., 2012). Relative to its previous version, HadCRUT has greatly improved observational coverage in the Arctic (Morice et al., 2012). However, the observation still is relatively limited in the Arctic, especially in the early times.

Interpolation is often used to fill the gaps in coverage in the observation data sets. Cowtan and Way (2014) used the optimal interpolation to produce a long-term global coverage of SAT based on HadCRUT4. However, interpolated Arctic SAT with observations at middle and low latitudes may also include new bias. Huang et al. (2017) utilized the method Data INterpolating Empirical Orthogonal Functions reconstructed a full coverage of Arctic SAT by incorporating International Arctic Buoy Programme/Polar Exchange at the Sea Surface Arctic observations into the global SAT of National Oceanic and Atmospheric Administration. These researches indicated that incomplete and time-varying observational coverage in the Arctic may result in a little cooling bias in the recent decades (Cowtan & Way, 2014; Huang et al., 2017; Simmons & Poli, 2015). However, interpolated data set by Cowtan and Way (2014) is only updated to 2014, and the reconstructed data set by Huang et al. (2017) only covers 1900–2014. Furthermore, we investigate the effects of incomplete observational coverage on the secular Arctic warming that we focus on in this work by comparing the results from 36 CMIP5 GCMs' simulations with full coverage and with observational coverage (here, the coverage of HadCRUT). Our result shows that the incomplete observational coverage has a statistically insignificant effect on the secular Arctic warming (the details seen in section 3.3). Therefore, we use HadCRUT as the observation in our work. In addition, 100 realizations from the HadCRUT were utilized to examine the observed Arctic SAT variation and its uncertainties. These realizations were produced by blending 100 SAT members of the CRUTEM4 and 100 SST members of the HadSST3 on a one-to-one basis. These members were generated by combining the observations with the corresponding errors arising from measurement biases and applied bias adjustments.

The 36 CMIP5 GCMs' monthly SATs (Supporting Information Table S1) come from experiments forced with the historical forcings and RCP8.5 (Representative Concentration Pathway [RCP]) scenario (van Vuuren et al., 2011). Most of the historical simulations of the CMIP5 GCMs ended in 2005. To be aligned with the observation in terms of time period, historical simulations were extended to 2017, in which RCP8.5 scenario projections were used after 2005 during which period the world's greenhouse gas (GHG) emissions are closer to the RCP8.5 than the other RCP scenarios (le Quéré et al., 2016; van Vuuren et al., 2011). In addition, the global mean SAT and Arctic sea ice extent (north of 70°N) in the period of 1880–2017 are also analyzed to identify their relationship with the Arctic SAT. In order to investigate the contribution of natural forcings and GHG forcings to the evolution of Arctic SAT over the past century, we also employed additional

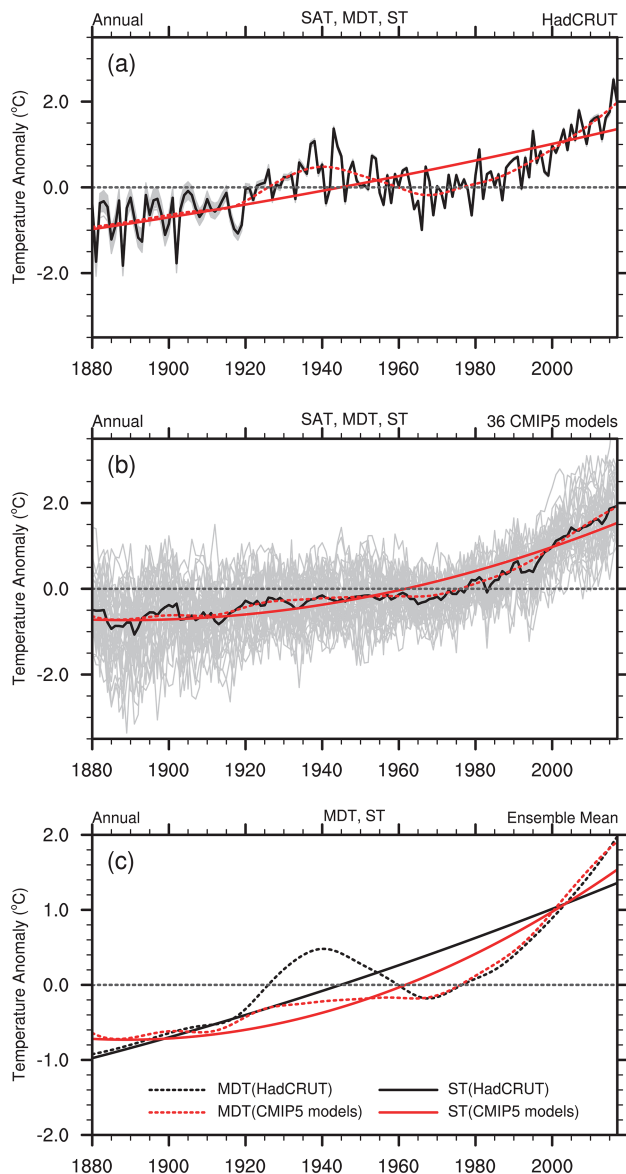


Figure 1. The annual Arctic SAT anomalies over 1880–2017 and MDT, ST of the annual Arctic SAT based on ensemble empirical mode decomposition analysis, for (a) the HadCRUT and (b) the CMIP5 global climate models historical simulations. Gray curves represent 100 realizations from the HadCRUT in (a) and the 36 CMIP5 global climate models' simulations in (b), respectively; the black curves are the ensemble mean of HadCRUT realizations; red thick dash and solid lines represent corresponding simulated MDT and ST of CMIP5 GCMs, respectively. The multi-decadal variabilities and STs from (a) and (b) are collected in (c) separately with black and red colors. SAT anomalies are relative to 1961–1990. CMIP5 = Coupled Model Intercomparison Project Phase 5; MDT = multi-decadal trend; SAT = surface air temperature; ST = secular trend.

forcing simulations from 17 out of the above 36 CMIP5 GCMs, which include experiments driven with the historical forcings (His), only natural forcings (Nat), and only GHG forcings (GHG; Table S1). Due to the fact that most simulations in Nat and GHG experiments ended in 2005, all of these simulations were only analyzed for the period of 1880–2005. Before the analysis, all the simulated monthly SATs were firstly converted to anomalies relative to 1961–1990 reference period as same as for the HadCRUT, and then the data were regridded to the observational grids and masked by the observational coverage to be consistent with the spatial and temporal coverage of the observation (HadCRUT). The Arctic SAT series is calculated with available gridded observations with area weight.

EEMD is developed from EMD (empirical mode decomposition) and can decompose data time series into intrinsic mode functions (IMFs) and a residual (Wu et al., 2011). IMFs and the residual are manifested with oscillatory components on various time scales and a nonlinear, secular trend (hereafter ST), respectively, and they may reflect specific physical processes (Wu et al., 2007; Wu et al., 2011; Wu & Huang, 2009). In contrast to EMD, EEMD defines the decomposed components as the mean of an ensemble of decompositions, each of which is consisted of the data time series plus a white noise of finite amplitude. This process can rule out the influence of noise in the process of decomposition, which may result in significantly different decomposition in EMD analysis (Ji et al., 2014; Wu & Huang, 2009). Comparing to other methods, EEMD can extract the trend from data series, particularly from nonlinear, non-stationary data series without requiring any predetermined basis function. This method emphasizes the adaptiveness and temporal locality of the decomposition, implying that the decomposition will not change with the addition of new data (Wu et al., 2007; Wu et al., 2011). This property of EEMD is consistent with the reality that physical processes occurred in specific time intervals should not alter when the time series is extended with new data (Wu et al., 2007; Wu et al., 2011). In EEMD analysis, 0.2 standard deviations of the annual Arctic SAT series over 1880–2017 was used as the noise and 1,000 members were produced for each component. The ensemble mean (EM) of these 1,000 members was the decomposed component of EEMD. Consequently, six IMFs and one residual are obtained. Here, we adopted EEMD to extract the significant components of the Arctic SAT and to examine the performance of CMIP5 GCMs in simulating the anthropogenic contribution to the secular Arctic warming.

3. Results

3.1. EEMD Analysis and Secular Trend of Arctic SAT

We decomposed the annual Arctic SAT series into six IMFs and a residual with the method of EEMD (supporting information Figure S1). Following the methods by Wu et al. (2007) and Wu et al. (2011) respectively, both white noise and red noise significance tests consistently show that IMFs on the multi-decadal time scale (multi-decadal variability [MDV]) and the residual (ST), are statistically distinguishable from the

corresponding components of pure white noise and red noise (Figures S2 and S3). This means that these two components most likely represent physically meaningful signals. In Figure S4, it is obvious that ST represents the warming on the global scale, while MDV describes the multi-decadal oscillation mainly located in the North Atlantic Ocean. The sum of MDV and ST is defined, here, as a multi-decadal trend (MDT). As shown in Figures 1a and 1c, MDT can capture well the stepwise rise of the observed Arctic SAT in the past century, while ST reasonably represents the nonlinear, secular trend of the observed Arctic

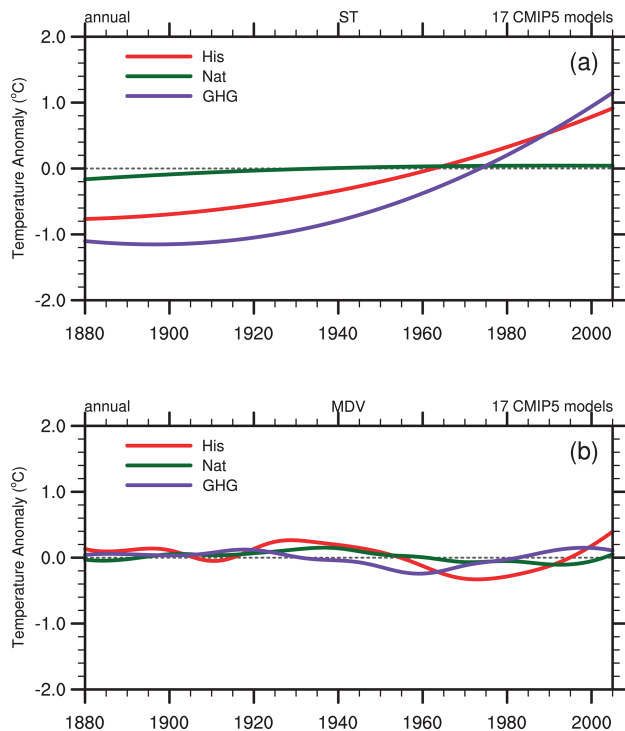


Figure 2. The ensemble mean of STs and MDVs from the 17 CMIP5 GCMs' simulations over 1880–2005, respectively for the historical, only Natural forcings, only greenhouse gasses forcing experiments. CMIP5 = Coupled Model Intercomparison Project Phase 5; MDT = multi-decadal trend; ST = secular trend.

warming. Similarly, MDT and ST also can capture the major variabilities of the simulated Arctic SAT from the CMIP5 models (Figures 1b and 1c).

In climate analysis, multi-model average of simulations from a large number of climate models can be used to represent the signal of external forcings due to internal variability effectively being averaged out (Dai et al., 2019; Frankcombe et al., 2018). Here, we calculate the EM of 17 out of the above 36 CMIP5 GCMs for forcing experiments His, Nat, and GHG, respectively. From Figure 2a, it is very clear that the anthropogenic forcings almost dictate ST of the Arctic SAT during the past century, while the natural forcing has little contribution. In respect of MDV, our analysis shows that both natural and anthropogenic forcings have a great influence on the evolution of MDV in the past century (Figure 2b). On the other hand, previous work (Fyfe, von Salzen, et al., 2013; Yamanouchi, 2011) indicated that internal variability also contributes to the multi-decadal variations of the Arctic SAT, such as the warming in the 1940s. This is also evident in Figure 1c, which shows that the combination of natural and anthropogenic forcings cannot totally explain the amplitude of the Arctic warming and cooling in the 1920s–1940s and 1940s–1960s respectively. Therefore, it can be concluded that the ST of the Arctic SAT almost exclusively stems from anthropogenic forcings, which most likely dominates the long-term warming in the Arctic, while MDV can be considered the resultant of internal variability and the natural forcings as well as anthropogenic forcings.

3.2. Contribution of ST and MDV to the Arctic Warming

The changes of MDT, MDV, and ST were examined for the past century. As shown in Figure 3a, the Arctic SAT (MDT) has increase 2.90 ± 0.11 °C and 2.55 ± 0.78 °C ($\pm 1\sigma$ means one standard deviation) in 1880–2017 respectively for HadCRUT and CMIP5 GCM simulations. During this

period, the ST has contributed 2.33 ± 0.14 °C to the rise of the Arctic SAT in the observation, and the simulated ST shows a comparable contribution (2.26 ± 0.74 °C, Table S2) only with a slight cooling bias of -0.07 °C. However, this goes with a large model spread, which indicates that the CMIP5 multi-model EM works well in simulating the anthropogenically induced secular warming over the past century, although large spread still exists among these climate models. In addition, the observed MDV has contributed 0.57 ± 0.04 °C (about 20%) to the Arctic warming (2.90 °C) in the period of 1880–2017. This is consistent with the above conclusion that the ST dominates the long-term warming. However, the simulated MDV has only contributed 0.30 ± 0.34 °C to the simulated Arctic warming of 1880–2017, approximately 12% (Table S2). The contribution of the MDV to the Arctic warming is much lower in the EM of simulations than the observation, which may be partly due to exclusion of internal variability in the multi-model mean.

As shown in Figures 1c and S5, the evolution of the observed Arctic SAT in the past century can be divided into three periods: a warming in 1880–1940, followed by a cooling from 1941 to 1967, and a subsequently rapid warming in 1968–2017. For the EM of CMIP5 GCMs' simulations considered, the cooling is too weak and the recent warming starts 4 years earlier than the observation, from which the simulated MDT becomes positive. Most notably, however, the CMIP5 multi-model EM reproduces the most recent Arctic warming very well, closely following the evolution of the Arctic SAT in 1968–2017 (Figure 1c). The simulated MDT shows a warming of 2.08 ± 0.66 °C during 1968–2017 with a slight bias of -0.08 °C for EM relative to the observed MDT change (2.16 ± 0.03 °C; Figure 3b). By contrast, the simulated ST has a warming of 1.41 ± 0.46 °C in this period, which is larger than that of the observation (0.95 ± 0.03 °C). The difference between them is statistically significant at the 0.05 level. Further, most models (27 among the 36 CMIP5 models) produce larger ST changes during the period 1968–2017 than all of the 100 realizations of HadCRUT. Therefore, although the CMIP5 multi-model EM can reproduce well the Arctic temperature rising in 1968–2017, it significantly overestimates the anthropogenically induced secular warming. In respect of MDV, the observed MDV has contributed 1.21 ± 0.04 °C (56%) to the warming (2.16 ± 0.03 °C) in 1968–2017.

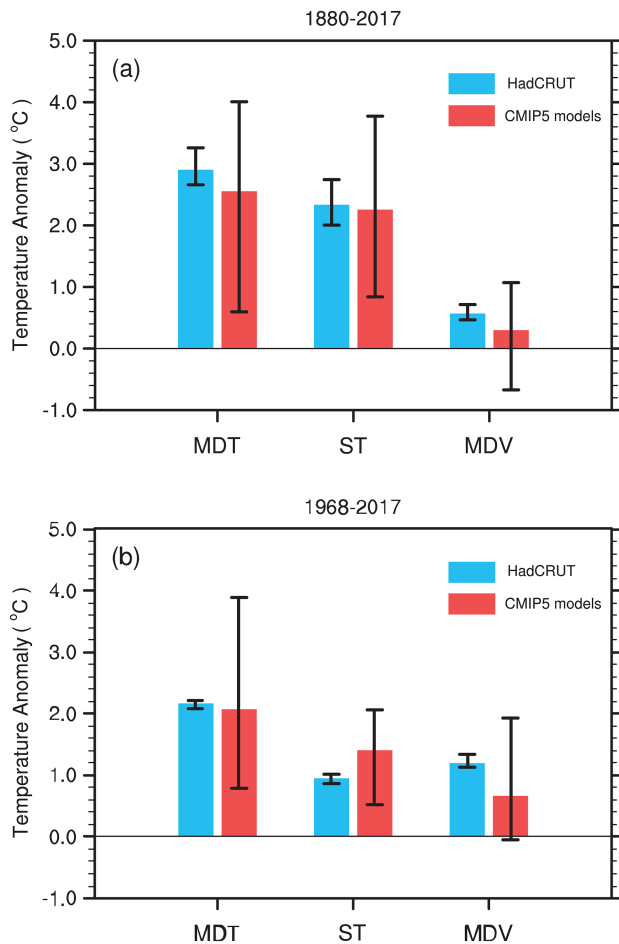


Figure 3. The warming respectively represented by the changes of MDT, ST, and MDV in the periods of (a) 1880–2017 and (b) 1968–2017. The blue and red columns represent contributions from the changes of MDT, ST, and MDV respectively for the HadCRUT and 36 CMIP5 GCMs' simulations. The vertical bars show the range of MDT, ST, and MDV changes respectively from 100 realizations of HadCRUT and 36 CMIP5 GCMs' simulations. CMIP5 = Coupled Model Intercomparison Project Phase 5; MDT = multi-decadal trend; MDV = multi-decadal variability; ST, secular trend.

By contrast, the simulated MDV has contributed 0.67 ± 0.39 °C warming, nearly one-third (32%), to the EM of the simulated Arctic warming in this period. The contribution of MDV to the Arctic warming is substantially smaller in the CMIP5 multi-model EM than in the observation. This also may be partly due to removal of internal variability from the multi-model EM.

3.3. Overestimate of Arctic Warming Rates in the CMIP5 Models

From the above analysis, we can conclude that the CMIP5 multi-model EM can reproduce well the anthropogenically induced secular Arctic warming of 1880–2017; however, it significantly overestimates the secular warming in the recent warming period (1968–2017). This may arise from the nonlinear response of the secular Arctic warming to the anthropogenic forcings, namely, that the ST varies with time. Therefore, we further examined the evolution of the ST during the period of 1880–2017. As shown in Figure 4a, the rate of the secular warming increases in the observation from 0.14 °C/10a in the early 1890s to 0.21 °C/10a in the mid-2010s. The simulated secular warming rate also grows but faster compared to that of the observation, as indicated by a negligible warming rate in the early 1890s and a relatively high warming rate of 0.35 °C/10a in the mid-2010s. Evidently, the mid-twentieth century appears to be a turning point for CMIP5 GCMs before which the CMIP5 multi-model EM underestimates the anthropogenic secular warming rate. After this time point, the simulated warming rate exceeds that of the observation and the disparity grows with the time, reaching 0.14 °C/10a in the mid-2010s.

The above analysis is based on SATs from the observation and the CMIP5 model simulations with observational coverage in the Arctic region. Both the incomplete data coverage in the Arctic region and SAT instead of SST used over open oceans may affect the calculation of the Arctic temperature (Cowtan et al., 2015; Huang et al., 2017). To estimate the impact of the incomplete coverage on the Arctic temperature change, we performed the same analysis based on the 36 CMIP5 GCMs' simulations with full coverage in the Arctic region. Figures S6 and S7 show that full coverage in the Arctic slightly increases MDT, ST, and MDV of the Arctic warming in both 1880–2017 and 1968–2017 and slightly enhances the secular warming rate at present relative to the incomplete coverage. However, their differences

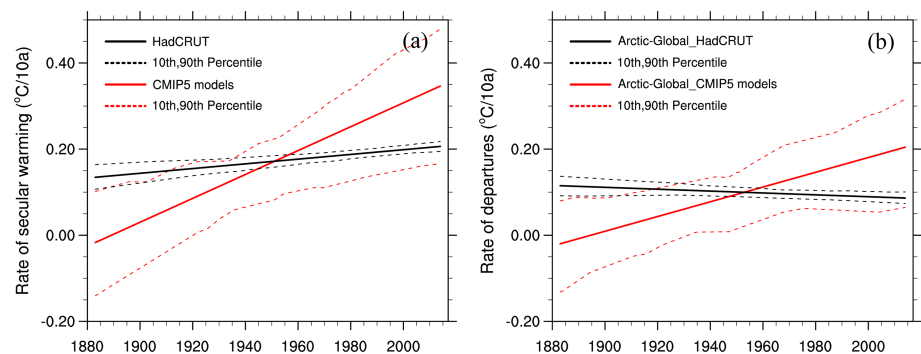


Figure 4. The rates of (a) the Arctic secular warming and (b) the departure of Arctic SAT ST from the global SAT ST during 1880–2017, estimated with their 7-point moving linear trend. The black and red solid lines represent ensemble mean of (a) the secular warming rates and (b) the rates of the departure of Arctic SAT ST from the global SAT ST for the 100 realizations of the HadCRUT and 36 CMIP5 GCMs' simulations, respectively. The black (red) dash lines denote their 10th–90th percentiles for 100 HadCRUT realizations and 36 CMIP5 GCMs' simulations, respectively. CMIP5 = Coupled Model Intercomparison Project Phase 5.

are not statistically significant at the 0.10 level. In addition, similar results were also obtained for the simulated ST in 1880–2017 by using full coverage data in the Arctic and SST instead of SAT over open oceans (Figure S8). This demonstrates the robustness of the conclusion that anthropogenically induced secular warming has been overestimated by the CMIP5 GCMs during the most recent warming period, and the overestimation is aggravated with time.

3.4. Overestimate of the Contribution of Sea Ice Loss

Recently, Dai et al. (2019) indicated that the Arctic sea ice loss plays a central role in Arctic amplification. Without the Arctic sea ice melting, the evolution of the Arctic SAT is similar to that of the global mean SAT (see figure 6 in Dai et al., 2019) under increasing CO₂. Thus, the additional warming of the Arctic relative to the global mean can be used to approximately represent the contribution from Arctic amplification induced by the Arctic sea ice loss. As shown in Figure S9, the departures in the ST of the Arctic SAT relative to the global mean SAT grow with time in both the observation (HadCRUT) and 36 CMIP5 model EM. Likewise, the simulated ST of the annual Arctic sea ice extent also gradually rises in the past century. Further analysis shows that the rate of the additional Arctic warming relative to the global mean decreases slightly in the observation from 0.11 °C/10a in the mid-1890s to 0.09 °C/10a in the mid-2010s (Figure 4b). In contrast, the trend rises in the 36 CMIP5 model EM from a rate close to zero to 0.20 °C/10a at the corresponding times. Furthermore, the trend from the CMIP5 GCMs EM exceeds that of the observation since the mid-twentieth century. It is clear in Figures 4a and 4b that the overestimation of the secular Arctic warming rate during the recent decades in the CMIP5 GCMs mainly comes from the exaggerated contribution from the Arctic sea ice loss, although it can also be partly due to the overestimated global warming rate in the CMIP5 models (Figure S10). A similar conclusion is also obtained for the 36 CMIP5 model EM with complete coverage in the Arctic region and SST instead of SAT used in the open water area (Figures S8 and S11). Therefore, the above conclusion is robust as it is not affected by the data coverage. However, given the limited length of the observed Arctic sea ice, it is hard to figure out whether the overestimation of the secular Arctic warming rate mainly comes from the inaccurately simulated change of Arctic sea ice extent or effects of associated physical process under the increasing anthropogenic emissions.

4. Conclusion and Discussion

In this work, we found that the response of the Arctic SAT to the time-varying anthropogenic forcings is nonlinear, mainly manifested with a nonlinear secular warming trend on the long-term time scale, based on the observational data set HadCRUT and the 36 CMIP5 GCMs' simulations. The rate of this secular warming is intensified with time both in the observation and in the climate model simulations. Our results also indicate that CMIP5 GCMs EM overestimates the anthropogenically induced secular warming rate since the mid-twentieth century against the observation and the overestimation aggravates with time, although the GCMs EM can simulate well the increase of the Arctic temperature over 1880–2017. This finding implies that the future Arctic warming could have been over-projected by the CMIP5 models. Further analysis indicates that the exaggerated heating contribution from the Arctic sea ice melting in GCMs may have contributed to this overestimation. Given the important influence of Arctic climate change on the local and global environments as well as ecosystem (Cohen et al., 2014; Greene et al., 2008; Hanna et al., 2013), realistic representation of the nonlinear response of Arctic warming to the anthropogenic forcings is considered a key to the reliable future climate projection. In particular, accurately simulating the response of Arctic SAT to melting sea ice is the key to precisely project the future Arctic temperature.

However, there are also other local and remote feedbacks such as cloud, water vapor transport, and so forth (Hao et al., 2019; Jeong et al., 2014; Pithan & Mauritsen, 2014; Praetorius et al., 2018; Screen et al., 2012; Winton, 2006). These feedbacks may also play important role in the Arctic warming and need to be studied either. It is also noticeable that large spread still exists among the CMIP5 GCMs' simulations. Although the CMIP5 GCMs EM overestimate the secular warming rate in recent decades, the observed secular warming rate still locates in the range of those of CMIP5 GCMs' simulations and is close to the lower end (Figure 4a). In addition, some research (Fyfe, Gillett, & Zwiers, 2013) pointed out that the overestimation of the global warming in the early of 21st century by CMIP5 models may be partly due to errors in the prescribed external forcings. This may also affect the CMIP5 GCMs' simulations.

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