**Weakened Antarctic Dipole Under Global Warming in CMIP6 Models**

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**Abstract** The Antarctic dipole (ADP) depicts the leading mode of interannual variability over the Antarctic region in both sea ice and surface air temperature (SAT) fields. The ADP is superimposed on the long-term climatic trends, modulating the response of the mean climate to external forcing by modifying the signal-to-noise ratio. The response of the ADP to greenhouse warming is unknown. Based on the Coupled Model Intercomparison Project Phase 6 models that capture main characteristics of the ADP, we find a robust reduction in variability of ADP under greenhouse warming. The warming-induced sea ice loss limits the magnitude of ADP SAT variability through surface albedo feedback. The El Niño-Southern Oscillation (ENSO) and the Southern Annular Mode (SAM) are two main triggering mechanisms of the ADP on interannual time scale. In a warmer climate, decreased variability of the SAM contributes to weakened ADP but increased ENSO variability plays an offsetting role.

**Plain Language Summary** Anthropogenic forcing on the Antarctic climate is superimposed on internal variability. The Antarctic dipole (ADP) represents the leading internal variation mode of sea ice concentration and surface air temperature, featuring seesaw signals over the Pacific and Atlantic sector of the Southern Ocean. We find a weakened ADP under greenhouse warming in both sea ice and surface air temperature (SAT) fields. The weakening mainly arises from a warming-induced sea ice loss, limiting the development of SAT anomalies through the surface albedo feedback. In addition, declined surface pressure variations, which are a response to the SAM, also contribute to the weakening of the ADP. A projected increase in ENSO variability and slightly stronger correlation with the ADP indicates their offsetting role on the weakened ADP. The projected weakening in ADP variability in a warmer climate may expose a more sensitive Antarctic climate to external forcing. This finding also suggests a limit in interannual predictions of sea ice in a warming climate, owing to the suppressed signal magnitudes.

1. **Introduction**

Variability of Antarctic sea ice has far-reaching impacts on the ocean and atmosphere system not only in the high-latitude regions (Bader et al., 2013; England et al., 2018; Raphael, 2003) but also in the tropics (England et al., 2020). For example, the Antarctic sea ice modifies the atmosphere circulation through altered radiative properties, heat exchanges, and momentum flux at ocean-atmosphere interface (Wu & Zhang, 2011). The melting or freezing of sea ice may lead to variations of freshwater input to the ocean, affecting the global thermohaline circulation (Adusumilli et al., 2020). Outside of the mid- and high latitudes, the Antarctic sea ice loss exerts an impact on the tropics, inducing enhanced surface warming in the eastern Pacific and increased precipitation over the Pacific ITCZ region (England et al., 2020). Hence, understanding variability of Antarctic sea ice and atmosphere conditions in the context of global warming has profound climatic and ecological ramifications (Massom & Stammerjohn, 2010).

The Antarctic dipole (ADP) is the most prominent mode of interannual variability within the Southern Ocean, reflected in surface air temperature and sea ice fields (Holland et al., 2005; Yuan & Martinson, 2000, 2001). The ADP features seesaw-like signals between the central/eastern Pacific sector and the Atlantic sector of the Southern Ocean, mainly representing a standing wave in the western hemisphere of the Antarctic. The prevailing mechanism considers it as a manifestation of topical-polar teleconnection, arising from El Niño-Southern Oscillation (ENSO)-excited Rossby wave trains (Song et al., 2011; Turner, 2004; Yuan, 2004;...
Yuan et al., 2018). The southward propagating Rossby waves lead to anomalous surface pressure over the Amundsen Sea region, further affecting the heat transport and advection of sea ice.

In addition, the Southern Annular Mode (SAM) affects the ADP through altering the meridional movement of westerly jet in the Southern Hemisphere. On the one hand, it modulates the sea ice expansion by an anomalous Ekman drift (Stammerjohn et al., 2008). On the other hand, the swing of westerlies results in anomalous Ekman pumping, which bring subsurface water into the surface (Purich et al., 2016). Nevertheless, both ENSO and the SAM are changing in response to global warming, which may further induce changes of the ADP. Since interannual variability is superimposed on its low-frequency variability or trends, it may influence the response to external forcing by modifying the signal-to-noise ratio (Li et al., 2020). Thus, we seek to understand the response of the ADP variability change under global warming.

2. Data Sets and Methods

To evaluate the simulation of ADP in models, we use monthly sea ice concentration (SIC) from the fifth generation ECMWF reanalysis for the global climate and weather (ERA5), calculated for 1980–2014 (Hersbach et al., 2020). Also used are surface air temperatures (SATs) from the 20CRv3 data sets for the 1900–2014 period (Slivinski et al., 2019) and multimodel simulations of the above two fields from the Coupled Model Intercomparison Project Phase 6 (CMIP6) historical outputs for the corresponding period with the observations (Eyring et al., 2016). We consider a model reasonably captures the observed characteristics when it meets two criteria: significant spatial correlations (cor > 0.4) and similar periodicity. Then, we use the select models to carry out the following analysis.

To examine the impacts of global warming on variability of the ADP, we use three future warming scenarios (SSP1-2.6, SSP2-4.5, and SSP5-8.5) in CMIP6 for the period 2015–2099, in which the radiative forcing reaches 2.6, 4.5, 8.5 W/m² in 2100 respectively. We concatenate data from the historical (1900–2014) and SSP1-2.6/SSP2-4.5/SSP5-8.5 (2015–2099) simulations from the CMIP6 models (Table S1), taking the period 1900–1999 as the present-day climate and the period 2000–2099 as the future climate. To focus on interannual variability, the seasonal cycle at each grid point is removed by subtracting the long-term monthly means and a 13-month low pass filter is applied. Trends at each grid point are removed by a quadratic regression, which is commonly used to eliminate the nonlinear trends (Cai et al., 2015, 2020).

Several climate indices are utilized to describe ENSO, the SAM. Niño3.4 indices in models are defined as the area-averaged SST anomalies among the region of 5°N–5°S, 170°–120°W, with a 5-months running mean employed (Trenberth, 1997). The SAM indices are described as difference of zonal mean sea level pressure between 40° and 65°S (Gong & Wang, 1999). Each month’s zonal mean is standardized by the mean/standard deviation determined for the climatological time period.

3. Results

3.1. Comparison of the Observed and the CMIP6-Simulated Antarctic Dipole

The observed sea ice component of the ADP, which is defined as the leading empirical orthogonal function (EOF) mode of sea ice edge anomalies (30% sea ice concentration), is examined using the SIC from ERA5. By regressing the SIC anomalies onto the normalized ADP index, the observed spatial structure features a dipole mode, with notable opposite signs over the Amundsen-Bellingshausen sea and the Weddell Sea (Figure 1a), in line with previous studies (Yuan & Martinson, 2001). We conduct similar analysis in CMIP6 models. Though with strong intermodel differences, most models, capture the spatial structure of the observed ADP (Figure S1). Here, we select models in which the spatial correlation coefficient exceeding 0.4. The multimodel ensemble mean (MMEM) pattern of selected models shows a high spatial correlation with the observation reaching 0.87 (Figure 1b). For the temporal characteristics, spectral analysis is applied to the ADP sea ice indices of the selected models (Figure 1c). The observed power spectrum displays significant power on interannual time scales, with a spectrum peak on the order of 3 years. Compared with the observation, the selected CMIP6 models generally capture the interannual oscillations, with some disparities in individual models. All models exhibit the power spectrum peaks at 2–5 years. Overall, the CMIP6 models...
simulate comparable spatiotemporal features of the ADP with observations. Thus, we use the selected models to conduct our analysis.

For the SAT counterpart, the Antarctic dipole is presented as the leading two EOF modes of SAT anomalies along the 65°S (Yuan & Martinson, 2001). Thus, we construct an ADP SAT index by adding the normalized leading two principal components. Next, we derive the spatial structure by regressing the SAT anomalies onto the ADP index. In observation, the spatial structure displays strong opposite signals over the Amundsen-Bellingshausen sea and the Weddell Sea, explaining 45.3% of the total variance (Figure 1d). But not all

**Figure 1.** Spatiotemporal features of the Antarctic dipole (ADP) in observation and CMIP6 “historical” multimodel simulations. The ADP reflects in sea ice concentration (SIC) and surface air temperature (SAT) fields. (a) Spatial pattern of the leading empirical orthogonal function (EOF) mode of detrended SIC in observation, for the period 1979–2014 (unit: %). (b) Same as panel (a), but for the CMIP6 MMEM. (c) Power spectra of the ADP SIC indices as a function of periodicity (months) for the observation and the individual models in the historical period. Only models with spatial correlation coefficient exceeding 0.4 are shown here. Only significant power values (P < 0.05) are shaded. (d) Spatial pattern of the leading EOF mode of detrended SAT in observations, for the period 1900–2014 (unit: °C). (e) Same as panel (d), but for the CMIP6 MMEM. (f) Same as panel (c), but for the SAT.
models reproduce the dipole-like feature as seen in observation (Figure S2). Hence, the models in which spatial correlation is smaller than 0.4 are not selected. The MMEM of selected CMIP6 models show good performance in simulating the dipole structure (Figure 1e). Moreover, a spectrum analysis reveals significant interannual variability in observation, with power peaks between 3 and 5 years, which can also be seen in the above selected models (Figure 1f).

3.2. Reduced Variability of the ADP Under Global Warming

The dipole structure is the key oscillation mode over the Antarctic region within the historical record, but how it will change in response to the ongoing climate change remains unclear. Based on the concatenated data from historical and SSP5-8.5 scenarios, we assess the spatial distribution of MMEM change ratio in the standard deviation (s.d.) of SIC and SAT between the present-day (1900–1999) and future (2000–2099) 100-year periods in the 16 selected models (red and blue bars). The reduction ratio of each model is marked as the black hexagram (unit: %). Models with variance change not exceeding the 95% confidence level are grayed out. (c) Same as panel (a), but for the SAT fields. (d) Same as panel (b), but for the ADP SAT indices in the 23 selected models.

Figure 2. Projected decrease in the Antarctic dipole (ADP) variability. (a) Multimodel ensemble mean (MMEM) map of the change ratio in terms of standard deviation of sea ice concentration (SIC). The change ratio is calculated using Equation 1. Significance above the 95% confidence level is marked with dots. (b) Comparison of the standard deviation of the ADP SIC indices between the present-day (1900–1999) and future (2000–2099) 100-year periods in the 16 selected models (red and blue bars). The reduction ratio of each model is marked as the black hexagram (unit: %). Models with variance change not exceeding the 95% confidence level are grayed out. (c) Same as panel (a), but for the SAT fields. (d) Same as panel (b), but for the ADP SAT indices in the 23 selected models.
To directly demonstrate the ADP variability changes, we calculate the standard deviation change ratio in the ADP sea ice/SAT indices between present-day and future climate (Figures 2b and 2d). For the SIC component, all the selected models display a significant variability reduction (above the 95% confidence level), with the change ratio ranging from −6.1% to −33.9% (Figure 2b). Similarly, the SAT ADP indices in all models show reduced variability, for the decreased level ranging from −8.2% to −33.2% (Figure 2d). Considering the ADP has clear seasonal feature, we also examine ADP variability in each season (Figures S3 and S4). Weakened ADP variability exists in all seasons, in agreement with the previous monthly results. To further verify that the above results are not dependent on the warming scenarios, we also examine outputs from the SSP1-2.6 to SSP2-4.5 scenarios (Figures S5 and S6). ADP variability features a greater decrease as the warming intensifies.

Thus, there is a robust decrease in ADP variability under global warming, with a strong intermodel consensus. In this study, we will discuss possible mechanisms in forcing the weakened ADP under greenhouse warming.

### 3.3. The Role of the SIC Mean State Change

For the ADP sea ice component, the warming-induced sea ice loss could directly limit the magnitude of SIC variability. Furthermore, the sea ice loss may also induce changes in SAT variability. In a warmer climate, most coupled ocean-atmosphere models show more surface warming in the mid-to-high latitudes than the tropics, which is referred to as the “polar amplification” (Holland & Bitz, 2003). This is mainly contributed by a positive surface albedo feedback (SAF) in the polar region (Screen & Simmonds, 2010). As the climate continues to warm, sea ice or snow retreat exposes more ocean or land surfaces, which less reflective of solar radiation. This extra absorption of solar radiation accelerates the warming, leading to further melting of sea ice or snow.

The presence of sea ice also exerts an influence on the magnitude of SAT fluctuations. For example, the presence of SAF increases the local SAT variability at a level of 20% along the Southern Hemisphere sea ice margin during all seasons (Hall, 2004). Hence, the retreat of sea ice in the warming climate potentially reduces SAT variability because the capacity in SAF is substantially reduced. By examining the SIC climatological mean state change ratio between the present-day and future climate (Equation 2), we find a significant reduction of sea ice in the future climate, particularly in the ice edge region (Figure 3a).

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\text{Change ratio} = \frac{\text{mean (future climate)} - \text{mean (present day)}}{\text{mean (present day)}}.
\]

Given that, we investigate the intermodel regression pattern of the SIC mean state change onto the ADP SAT index changes across models. As shown in Figure 3b, significant positive anomalies appear in the ADP-dominant South Pacific and South Atlantic sector, suggesting a close linkage between the weakened ADP and the SIC reduction. We further compare the ADP SAT index changes with the area-averaged SIC reduction over the ADP key region (Pacific: 68°–60°S, 140°–60°W and Atlantic: 55°–50°S, 60°–0°W) in individual model, and find that they are significantly correlated at 0.52 (p = 0.036) (Figure 3c). In other words, a greater loss of Antarctic sea ice corresponds to weaker ADP variability.

### 3.4. Relationships With the ENSO

A mounting body of studies has proposed the ENSO-related teleconnection structure in determining the ADP (Schneider et al., 2012; Simpkins et al., 2012; Stammerjohn et al., 2008; Yuan, 2004). Hence, we examine if this teleconnection exists in the CMIP6 models between the present-day and future climate. By regressing the SST anomalies onto the ADP indices, an El Niño-like warming emerges in the central and eastern tropical Pacific (Figure 4a). In addition, the SLP regression pattern shows the Pacific-South America pattern (Figure 4b), which has long been recognized as ENSO-excited quasi-stationary Rossby wave trains in the mid-to-high southern latitudes (Irving & Simmonds, 2016; Mo & Higgins, 1998). Thus, the above results highlight the well-simulated ENSO’s role in determining the ADP in CMIP6 models.
However, variability of ENSO is increasing under the warming climate, which has been widely documented in prior studies (Cai, Santoso, et al., 2015; Cai, Wang, et al., 2015; Cai et al., 2018, 2020). This may alter the ENSO’s influence on the ADP under global warming. Based on the CMIP6 data sets, we perform a correlation analysis of SLP anomalies with the Niño3.4 index during the present-day and future climate respectively. Similar significant dipole structures exist in the Antarctic region during these two periods, with slightly stronger correlations in the future climate (Figures 4c and 4d). In addition, we compare the standard deviation of tropical Pacific SST variability using two metrics. The MMEM SST standard deviation change ratio distributions reveal increased variability within the tropical region, with the central Pacific showing the strongest intensification with a 40% increased variability (Figure 4e). To illustrate the intermodel performance, we calculate the standard deviation of the Niño3.4 indices in two periods, as well as its change ratio (Figure 4f). Fifteen out of 21 models (71%) generate a statistically significant increase in variability, indicating the intermodel consensus on the robust intensified variability of the tropical Pacific SST. Combining the above two factors, the role of tropical Pacific SST is to intensify the ADP, indicating its offsetting role on the weakened ADP. Thus, the attenuation of ADP variability is driven by other mechanisms.
In addition to ENSO, the SAM, representing the leading intrinsic oscillation mode of the Southern Hemisphere atmosphere, also modulates the ADP on the interannual time scales (Holland et al., 2005). Here, we focus on the effect of the SAM on ADP variability under global warming. We determine the changes of atmospheric circulation variability in response to warming, by investigating the spatial distribution of standard deviation change ratio of SLP anomalies (Figure 5a). We find weakened SLP anomalies located in most of the high latitude regions, with the most notable decline centered in the Amundsen Sea.

3.5. Relationships With the SAM

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decrease in SLP variability results in weakened Amundsen Sea Low (ASL) variability, contributing to the reduction of ADP variability.

To further elucidate the role of SAM, we compare the standard deviation of the SAM indices between present-day (1900–1999) and future (1999–2099) 100-year periods in the 23 selected models (red and blue bars). The reduction ratio in each model is marked by the black hexagram (unit: percentage %). Models in which variance change does not exceed the 95% confidence level are grayed out. (c) Map of correlation coefficients of surface air temperature anomalies with the SAM index for the period 1900–2099. Significance above the 95% confidence level is indicated by dots. (d) Scatter diagram of the projected changes in SAM (sign-reversed) versus changes in the Antarctic dipole (ADP) variability (sign-reversed). To enhance the intermodel comparability, we scale the changes by increase in global mean SST of each model. Linear fit (black solid line) is shown together with the correlation coefficient and p value from the regression.

Figure 5. (a) The multimodel ensemble mean of the change ratio in the standard deviation of SLP. The change ratio is calculated using Equation 1. (b) Comparison of the standard deviation of the SAM index over the present-day (1900–1999) and future (1999–2099) 100-year periods in the 23 selected models (red and blue bars). The reduction ratio in each model is marked by the black hexagram (unit: percentage %). Models in which variance change does not exceed the 95% confidence level are grayed out. (c) Map of correlation coefficients of surface air temperature anomalies with the SAM index for the period 1900–2099. Significance above the 95% confidence level is indicated by dots. (d) Scatter diagram of the projected changes in SAM (sign-reversed) versus changes in the Antarctic dipole (ADP) variability (sign-reversed). To enhance the intermodel comparability, we scale the changes by increase in global mean SST of each model. Linear fit (black solid line) is shown together with the correlation coefficient and p value from the regression.

decrease in SLP variability results in weakened Amundsen Sea Low (ASL) variability, contributing to the reduction of ADP variability.

To further elucidate the role of SAM, we compare the standard deviation of the SAM indices between present-day and the future climate in CMIP6 models. In the future period, 17 of the 23 selected models (74%) simulate a statistically significant (above 95% confidence level) decrease in the SAM index variance, with the ensemble-mean reduction ratio is 7.8% (Figure 5b). Moreover, we conduct a correlation analysis of SAT anomalies with the SAM index (Figure 5c). A dipole-like structure over the South Pacific and South Atlantic sector indicates the SAM’s contribution to ADP variability. Thus, we inspect the projected changes in the SAM and its relationship with the weakened ADP. As shown in Figure 5d, all but two of the models project a decrease in SAM variability, coherently with the weakening of the ADP. They are significantly correlated among models, with correlation coefficient of 0.58 (p = 0.005). A question arises as to whether the SAM is a cause or a consequence of the weakened ADP. A lead-lag correlation analysis between them finds that most of the models show the largest correlation when the SAM leads the ADP by one or two months. Thus, the projected reduction in SAM variability contributes to the weakening in ADP variability under greenhouse warming, explaining 33.6% of variance in the ADP reduction across models.
4. Conclusions

We find a robust decrease of ADP variability in the future climate among CMIP6 models, with a strong intermodel consensus. Large-scale modes of ENSO and the SAM are two dominant factors in triggering ADP variability. An increase in tropical Pacific SST variability, together with a slightly stronger correlation between ENSO and the ADP, suggests an offsetting rule of change ENSO in the weakening of the ADP. In contrast, a projected decreased variability of the SAM contributes to the reduction of the ADP through the ASL. In addition, the presence of SAF amplifies local SAT variability in Southern Hemisphere during all seasons, but the Antarctic sea ice reduces in the future climate, suppressing the SAF process, further limiting SAT variability. Our results suggest that the projected weakened ADP variability in a warmer climate may expose a more sensitive Antarctic climate to external forcing. Further, the reduction in ADP variability amplitude makes prediction of interannual predictions sea ice variability more challenging.

Data Availability Statement

Data used in this study can be downloaded from the websites below: ERA5: https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5; 20CRv3: https://psl.noaa.gov/data/gridded/data.20thC_ReanV3.html; CMIP6 data sets: https://esgf-node.llnl.gov/search/cmip6/.

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