The Southern Annular Mode and Southern Ocean Surface Westerly Winds in E3SM

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Abstract Climate variability and change in the Southern Hemisphere (SH) are influenced by the Southern Annular Mode (SAM) and are closely related to changes in the kinematic properties of the SH surface zonal winds. The SAM and SH surface zonal winds have strong effects on the atmospheric and oceanic circulation system. In this study we investigate the variability and trend in the SAM and position and strength of the surface zonal wind stress (TAUX), using two ensembles of simulations covering the historical record from the Energy Exascale Earth System Model (E3SM-HIST and Atmospheric Model Intercomparison Project) for 1979–2014. In addition, performance of two CO2 forcing simulations from the E3SM (E3SM-1pctCO2 and 4xCO2) is assessed to examine the sensitivity of the variability and changes in the SAM and SH surface TAUX to climate forcing. In general, all E3SM simulations tend to capture the dominant feature of the SAM pattern reasonably well. The annual SAM index in the E3SM-HIST simulation shows a significant increasing trend. These features are similar to the trends in the strength (along with poleward shift in the position) of the annual surface TAUX. For the climatological surface TAUX position and strength, the two CO2 forcing simulations show slightly poleward movement and stronger intensity, while the E3SM-HIST is equatorward and weaker than observations. In the relationship between the SAM and surface TAUX, we show that the SAM index exhibits a positive (negative) relationship with the strength (position) of the surface TAUX in the variability for all seasons and annual mean.

1. Introduction

The Southern Annular Mode (SAM), which is often referred to as the Antarctic Oscillation, has strong effects on the climate systems at high and middle latitudes of the Southern Hemisphere (SH; Gong & Wang, 1998; 1999; Thompson & Wallace, 2000; Thompson, Wallace, & Hegerl, 2000). The SAM displays a seesaw pattern for the atmospheric mass (sea level pressure (SLP) or geopotential heights) in extratropical regions over the SH. The positive phase of the SAM is characterized by lower anomalous air pressure over the Antarctic along with higher anomalous pressure over the middle latitudes. With changes in air pressure distribution, changes in the strength and position of the westerly winds can occur. In the positive SAM phase, the westerly winds are stronger and move poleward, while the westerly winds weaken in the negative phase and move toward the equator.

Researchers have used a variety of methods to define the dominant mode of atmospheric variability in the SH. Gong and Wang (1999) suggested that the SAM is defined as a difference between the zonal mean SLP at 40°S and 65°S. A definition of the SAM as the leading empirical orthogonal function (EOF) of the 850-hPa geopotential height (poleward of 20°S) was reported by Thompson and Wallace (2000), and some other researchers have also used the geopotential height at 500 hPa (Cai & Watterson, 2002) or SLP (Cai & Cowan, 2007; Miller et al., 2006) to study SAM in the EOF-based framework.

Changes in the SH surface zonal winds have been related not only to changes of the oceanic circulation in the Southern Ocean (Biastoch et al., 2009; Gille, 2008; Marshall & Speer, 2012) but also variability and changes in the SAM (Hartmann & Lo, 1998; Monahan & Frye, 2006; Swart & Frye, 2012; Swart et al., 2015; Thompson & Wallace, 2000; Thompson et al., 2011; Yang et al., 2016). Studies of atmospheric reanalyses and simulations have found a poleward intensification of the surface westerly winds in the SH during the last decades, as a trend that is projected to continue during the 21st century (Swart & Frye, 2012; Swart et al.,...
2015; Yang et al., 2016). These facts are closely associated with a trend toward the positive phase of the SAM (Marshall, 2003; Thompson & Solomon, 2002).

Many studies (Fyfe & Saenko, 2006; Swart & Fyfe, 2012; Russell et al., 2006) have shown systematic biases of the variability and trends in the SH surface zonal winds using the climate models participating in the Coupled Model Intercomparison Project Phase 3 (CMIP3) and Phase 5 (CMIP5). The SH westerlies simulated by the CMIP3 and CMIP5 models were weaker than average in strength and equatorward in position compared to observations and reanalyses. The position of westerlies in this and similar studies is defined as the latitude of the maximum in the zonal mean surface zonal wind stress (TAUX) over the SH.

According to many studies (Arblaster et al., 2011; Kushner et al., 2001; Lu & Zhao, 2012), the intensity of the model's SH circulation is strongly associated with global warming, such as external CO₂ forcing. The increasing CO₂ forcing leads to increasing strength of the wind circulation. In addition, this relationship affects the SAM as the dominant mode of variability that is constrained by the pressure gradient. Prior to our study, we first checked model characteristics for the SH atmospheric circulation response to increasing CO₂ in Energy Exascale Earth System Model (E3SM) simulations (Figure S1 in the supporting information). It can be seen that the enhanced climatological circulation of zonal wind for increasing CO₂ in E3SM simulations is consistent with the results of the previous studies.

To further investigate the SH ocean circulation and atmospheric variability in E3SM simulations, we analyze the characteristics of the SAM and SH surface westerly winds. We use four different experiments (HIST, Atmospheric Model Intercomparison Project [AMIP]-type, 1pctCO₂, and abrupt-4xCO₂ data) from the E3SM simulations and two reanalyses over the period of 36 years in the satellite era to evaluate the performance of the variability and trends in the SAM and SH surface westerly wind stress. The aim of this study is to provide insight into SH climate variability in both historical and future periods and to contribute to the analysis and improvement of E3SM.

In the following section we introduce the reanalysis data, the E3SM model and simulations, and the methods employed in this study. In section 3, we consider how well the E3SM simulations reproduce the spatial pattern and temporal evolution of the SAM as well as the linear trend. Section 4 presents the interannual variability and trend of the maximum strength in the SH surface westerly wind stress and its latitudinal position. Analysis of the relationship between the SAM variability and properties of the SH surface westerly wind is discussed in section 5. Finally, a summary and conclusions are given in section 6.

2. Data and Methods

2.1. Model Description and Simulations

The E3SM, formerly known as the Accelerated Climate Modeling for Energy, is a new global coupled climate model funded by the U.S. Department of Energy. E3SM is the first climate system model that is capable of regional refinement of the horizontal grid for all components. The model uses unstructured-mesh arrays where neighbors are defined by pointer variables rather than structured meshes on regular latitude/longitude grids. Model components include the Model for Prediction Across Scales for ocean (Petersen et al., 2015; Reckinger et al., 2015; Ringler et al., 2013), sea ice (Hunke & Dukowicz, 1997), and land ice (Hoffman et al., 2018) and the spectral element dynamical core (Dennis et al., 2012; Tang et al., 2019) for the atmospheric component. More information appears in Table S1. The atmospheric resolution is ne30 (about 1° or 100 km) in the horizontal, with 72 vertical layers, and the ocean resolution varies from 30 to 60 km with 60 vertical layers. Detailed descriptions of E3SM simulations have been published for the atmosphere (Tang et al., 2019), ocean and sea ice (Petersen et al., 2019), land ice (Hoffman et al., 2018) and fully coupled simulations (Golaz et al., 2019).

We use four different types of E3SM simulations. They are part of the Diagnostic, Evaluation and Characterization of Klima (DECK; Eyring et al., 2016) experiments covering at least the period from 1979 to 2014. The historical simulations (hereafter HIST) contributing to the CMIP6 (Eyring et al., 2016) can be used to better understand climate change arising from natural forcing, anthropogenic forcing, and unforced variability. These simulations over the period 1850–2014 are forced by externally imposed conditions such as solar variability, volcanic aerosols, and human-induced changes (greenhouse gases and anthropogenic aerosols) based on observations. The AMIP (Gates et al., 1999) simulations are useful for the evaluation of the skill of the atmospheric model component. The simulations are constrained by the observed sea surface temperature (SST) and sea ice concentration. The remaining two simulations used in this study are...
Table 1

| Experiment name (Short name) | Forcing and specific experimental design | Simulation period (year) | Purpose/contribution |
|-----------------------------|------------------------------------------|--------------------------|----------------------|
| CMIP6 Historical simulation (HIST) | -CO₂ concentration, a natural forcing, b anthropogenic forcing, unforced variability | 1850–2014 | Understanding of climate change and evaluation |
| Atmospheric Model Intercomparison Project simulation (AMIP) | -CO₂ concentration, a natural forcing, b anthropogenic forcing, unforced variability | 1870–2014 | Evaluation of the atmospheric component |
| Abrupt quadrupling CO₂ simulation (4xCO₂) | -CO₂ abruptly quadrupled and held fixed | 1–155 | Characterizing of climate sensitivity |
| 1% CO₂ increase simulation (1pctCO₂) | -Gradually CO₂ increase at a rate of 1% per year, starting from 1850 value in the piControl | 1–150 | Model response under more realistic CO₂ forcing |

aNatural forcing: solar variability and volcanic aerosols. bAnthropogenic forcing: CO₂ concentration, aerosols, and land use.

The idealized CO₂-forced experiments in the DECK. They are branched off from the preindustrial control (piControl; Eyring et al., 2016; Stouffer et al., 2004) simulation, which holds the value of the atmospheric CO₂ concentration fixed at 1850 level during the entire experiment. In an abrupt quadrupling CO₂ simulation (hereafter referred as 4xCO₂), the CO₂ concentration is abruptly quadrupled and held fixed. This simulation is useful for characterizing the climate sensitivity of the model and the radiative forcing that arises from an increase in atmospheric CO₂ as well as changes that arise indirectly due to the warming. In a 1% CO₂ increase simulation (1pctCO₂; Meehl et al., 2005), the CO₂ concentration is gradually increased at a rate of 1% per year. This simulation is designed for studying model responses under more realistic forcing than the 4xCO₂ simulation. Table 1 briefly shows a description for CMIP6 and DECK experiments.

For this study, we use the SLP and surface zonal wind stress (TAUX) for the 36-year period of 1979–2014 for HIST and AMIP simulations, Years 115–150 for 1pctCO2 and 120–155 for 4xCO2 simulation. The same variables and period (36 years of 1979–2014) as model simulations are used for the two reanalyses (Table 2).

Table 2

Data List of Reanalyses and E3SM Simulations Used in This Study

| Reanalyses     | Energy Exascale Earth System Model (E3SM) simulations |
|----------------|------------------------------------------------------|
| ERA-Int        | NCEP-R1                                               |
| HIST (aEM: 5)  | AMIP (aEM: 3)                                        |
| 1pctCO₂ (aEM: 1) | 4xCO₂ (aEM: 1)                                    |

| Variables | Resolution (lon × lat) | Periods (year) |
|-----------|------------------------|----------------|
| Sea level pressure (SLP) | 480x241 (SLP) | 1979–2014 (36 years) |
| Surface zonal wind stress (TAUX) | 144 × 73 (SLP) | 1979–2014 (last 36 years) |
| TAUX (256 × 128) | 192 × 94 (TAUX) | 115–150 (last 36 years) |
| TAUX (256 × 128) | 192 × 94 (TAUX) | 120–155 (last 36 years) |

aEM: number of ensemble member.
Figure 1. Spatial pattern of the SAM as the leading EOF mode at the annual mean sea level pressure (SLP) south of 20°S, obtained from two reanalyses (a) ERA-Int and (b) NCEP-R1, and four E3SM simulations (c) E3SM-HIST, (d) E3SM-AMIP, (e) E3SM-1pctCO2, and (f) E3SM-4xCO2. The numbers above each panel indicate the explained variance. The spatial pattern correlation coefficients against the observed patterns are given at the upper right corner of the panel.

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and September to November (SON)), respectively (e.g., annual mean index is calculated as a simple average from 12 monthly mean indices). We use 35 seasonal samples for each season due to a lack of the DJF season of the last year (such as 2014D-2015JF).

2.2. Reanalyses
To evaluate the performance of the above-mentioned model simulations, observational data from two reanalyses are used: the National Centers for Environmental Prediction/National Center for Atmospheric
Figure 2. Annual mean SAM index (gray bar) defined as the corresponding time series of the first EOF mode in Figure 1 for the reanalyses, and (a) E3SM-HIST and (b) E3SM-AMIP ensemble means. The lines indicate the 5-year running average and the 95% confidence intervals about the E3SM-HIST (red) and E3SM-AMIP (blue) ensemble means are given by the shaded areas. Trends in the annual mean SAM index are shown at the right panel. The error bars show the 95% confidence interval of the trends for the E3SM-HIST (red) and E3SM-AMIP (blue) ensemble means.

Research reanalysis (NCEP-R1; Kalnay et al., 1996) and the European Centre for Medium-Range Weather Forecasts Interim reanalysis (ERA-Int; Dee et al., 2011). All the data sets used in this study are listed in Table 2.

2.3. Methods

2.3.1. Definition of the SAM

EOF analysis is one of the most common methods used to derive the SAM mode and indices. The SAM mode is defined as the leading EOF (the first component) of the SLP anomalies over a domain extending south of 20°S (Kostov et al., 2018; Zhou & Yu, 2004). The SAM index is the first principal component (PC) time series (PC1), which is the amplitude associated with the first eigenvector based on the covariance matrix. The SAM pattern is obtained by regressing the SLP anomalies onto the standardized SAM index calculated by subtracting the mean and dividing by the standard deviation (Fogt et al., 2009; Sen Gupta & England, 2006; Zheng et al., 2017; Zhou & Yu, 2004). For the HIST and AMIP simulations possessing several ensemble members, we take an ensemble average of each SAM pattern after obtaining the SAM mode by applying the same EOF analysis to each ensemble member.

2.3.2. Strength and Position of Surface Westerly Wind Stress

In order to calculate the strength and position of surface TAUX over the Southern Ocean, monthly mean surface TAUX data for the E3SM simulations and reanalyses are first interpolated onto a 0.5° × 0.5° horizontal grid, and then the land of the monthly surface TAUX data is masked. The strength of the Southern Ocean surface TAUX is defined as the maximum of the zonal mean surface TAUX between 70°S and 20°S. The latitudinal position of the surface TAUX over the Southern Ocean is taken as the latitude at the maximum of SH surface TAUX. To compute the annual and seasonal mean of the kinematic properties (strength and position) of the surface TAUX, the monthly kinematic properties are simply averaged. For calculating uncertainty in the time variability and trend of the ensemble mean simulations for the kinematic properties of the surface TAUX as well as SAM index, the confidence interval based on the variance of the ensemble mean is used (see supporting information for more detailed methods).

3. SAM Pattern, Variability, and Trend

3.1. Annual Mean SAM Pattern and SAM Index

The SAM patterns at the annual mean SLP south of 20°S in two reanalyses (ERA-Int and NCEP-R1) and four E3SM simulations (E3SM-HIST, E3SM-AMIP, E3SM-1pctCO2, and E3SM-4xCO2), which are often defined as the leading EOF mode of SLP (Caï & Cowan, 2007; Kostov et al., 2018; Miller et al., 2006; Zhou & Yu,
|              | Trend (ANN, hPa per decade) | Trend (MAM, hPa per decade) | Trend (JJA, hPa per decade) | Trend (SON, hPa per decade) | Trend (DJF, hPa per decade) |
|--------------|----------------------------|-----------------------------|----------------------------|-----------------------------|----------------------------|
| ERA-Int      | 0.30                       | 0.56                        | -0.08                      | -0.10                       | 0.78*                      |
| NCEP-R1      | 0.21*                      | 0.30*                       | 0.16                       | 0.07                        | 0.24*                      |
| E3SM-HIST    | 0.27*                      | 0.16*                       | 0.24*                      | 0.29*                       | 0.38*                      |
| E3SM-AMIP    | 0.18*                      | 0.22                        | 0.14                       | 0.24                        | 0.18                       |
| E3SM-1pctCO2 | 0.07                       | -0.11                       | -0.02                      | 0.05                        | 0.40                       |
| E3SM-4xCO2   | -0.23                      | -0.02                       | 0.03                       | -0.45                       | -0.35                      |

*Note. Asterisk (*) marks indicate statistical significance at the 95% confidence level in the Student two-tailed t test.*
Figure 3. As in Figure 2 but for (a) E3SM-1pctCO2 and (b) E3SM-4xCO2 simulations.

2004), are shown in Figure 1. The observed positive SAM patterns, characterized by lower SLP over Antarctica and higher SLP in the midlatitudes of the SH, can be seen in Figures 1a and 1b. The two reanalysis data sets indicate an almost identical SAM pattern, with a spatial pattern correlation of 0.961. Generally, the simulated SAM patterns in the E3SM reproduce observational features well (Figures 1c–1f), with a high pattern correlation coefficient against the two reanalyses. The values of the spatial pattern correlation against the ERA-Int are slightly higher in all simulations, as compared to those against the NCEP-R1. The leading modes of the annual mean SLP variabilities in the ERA-Int and NCEP-R1 explain 37.4% and 33.5% of the total variance, respectively. All the simulations, along with the E3SM-HIST accounting for the highest variance (44.5%), show higher explained variances than the observations. The E3SM-HIST and AMIP simulations show similar intensity in the strongest positive and negative centers compared to the observations and indicate lower center intensity than the two CO2 simulations (E3SM-1pctCO2 and 4xCO2). Note that the positions of the two centers in all simulations are similar to those in the observations. The sensitive response of the SAM pattern to increased CO2 forcing in model simulations can be also seen in many other studies (Arblaster & Meehl, 2006; Lu & Zhao, 2012; Stone et al., 2001). We have also analyzed the seasonal SAM patterns for the reanalyses and the simulations using the above-mentioned EOF method (Figure S2). For all the four seasons, all the E3SM simulations capture relatively well the dominant SAM features as the meridional dipole structure in SH extratropical regions. However, it can be seen that the SAM patterns of the simulations in austral spring and summer (SON and DJF) seasons are in a better agreement with the observations as compared to the ones in austral autumn and winter (MAM and JJA) seasons (Figure S2).

Figure 2 shows the temporal variability of the annual mean SAM index from the observed and simulated EOF PC1 time series of the annual mean SLP for the 36-year period of 1979–2014. Their SAM trends reflecting the long-term changes in the observations and model simulations are also examined. From Table 3, the quantitative correspondence between the simulated and observed trends of the SAM index can be found. Over 1979–2014 both ERA-Int and NCEP-R1 show a positive SAM trend in annual mean variability. The SAM trend in ERA-Int (0.3 hPa per decade) is larger than that in NCEP-R1 (0.21 hPa per decade). As noted by many studies (Gillett & Fyfe, 2013; Miller et al., 2006; Swart et al., 2015; Zheng et al., 2013) showing positive trend in the SAM over the recent historical periods, the HIST and AMIP simulations of the E3SM model have successfully reproduced the positive SAM trends that is significant at 95% confidence level, and the increasing trend of E3SM-HIST (0.27 hPa per decade) is located between the trends from the ERA-Int and NCEP-R1 (Figure 2 and Table 3). Swart et al. (2015) mentioned that the CMIP5 models in the SAM also exhibit positive trends on average, but the simulated increase generally appears lower than that seen in observations. It should be noted that the observations used, the data period used, and the SAM definitions in Swart et al. (2015) differ from this study. The annual mean SAM trend of the E3SM-AMIP (0.18 hPa per decade) is slightly lower compared with two observations. The E3SM-AMIP simulation also has a very close
relationship with the two reanalyses, showing a considerably high and significant correlation coefficients of 0.753 with ERA-Int and 0.816 with NCEP-R1. The reason for this is that AMIP simulations are forced by the observed SST and sea ice concentration.

The last 36 years of both 1pctCO2 and 4xCO2 simulations of the E3SM model produce a lower annual mean SAM trend relative to the two other simulations over the recent historical periods (Figure 3). The annual mean SAM index of E3SM-1pctCO2 simulation show a small and positive trend close to zero (0.07 hPa per decade). In contrast to the annual mean variability of the E3SM-HIST and AMIP simulations, a negative trend appears in the annual mean SAM index of the E3SM-4xCO2 simulation (Figure 3 and Table 3). Note that the trends in E3SM-HIST and AMIP as well as 1pctCO2 simulations carry the signals in response to time-varying forcings, while the trend in E3SM-4xCO2 simulation is likely due to adjustment to the abrupt external climatic changes by CO2 forcing (such as elimination of latitudinal warming differences in Cai et al., 2003), as well as model internal variability. They were not expected to be comparable. Cai et al. (2003) also found that during transient increase of CO2 concentration, the SAM exhibits a positive trend, but the SAM has trend-reversing feature after the CO2 concentration level is held constant. From that report, although several simulation conditions (simulation period, the model, CO2 forcing method, etc.) are different, we believe the same underlying cause can explain the difference in the annual mean SAM trends in the E3SM-1pctCO2 and 4xCO2 simulations seen in the present study.

### 3.2. Seasonal Mean SAM Index and Trend

To examine how well the E3SM simulations reproduce the variabilities and changes in the seasonal mean SAM index, we have depicted the seasonal SAM variability and trend for all simulations in Figure 4. In Table 3, we have quantified, along with significance test, the trend in the observed and simulated seasonal mean SAM indices. The reanalyses (except JJA and SON in ERA-Int) and both E3SM-HIST and E3SM-AMIP simulations show positive trends in the seasonal mean SAM index over the historical period (Figure 4e and Table 3), similar to the findings in previous report (Swart et al., 2015). The significant positive annual mean...

Figure 4. Seasonal mean SAM index (line) defined as the time series of the EOF PC1 for the two reanalyses and four E3SM simulations. The lines indicate the 5-year running average. The shaded areas envelop the 95% confidence intervals about the E3SM-HIST (red) and E3SM-AMIP (blue) ensemble mean simulations. Trends in the seasonal mean SAM index are shown at the bottom panel. The error bars show the 95% confidence interval of the trends for the E3SM-HIST (red) and E3SM-AMIP (blue) ensemble means.
SAM trends obtained from the E3SM-HIST simulations result from the significant positive trends in the seasonal mean SAM index that occur in all seasons. One of the reasons that the ERA-Int does not have significant annual mean trend like NCEP-R1 may be due to the negatively insignificant trends during JJA and SON. The negative trend in annual mean SAM of the E3SM-4xCO2 simulation may be largely affected by the negative SAM trends during SON and DJF seasons. The largest significant trends in observed seasonal mean SAM indices of ERA-Int and NCEP-R1 occur in DJF (0.78 hPa per decade) and MAM (0.3 hPa per decade), respectively. The E3SM-HIST simulation shows higher and significant trends relative to the two reanalyses in JJA and SON seasons. The seasonal mean SAM indices for E3SM-1pctCO2 simulation have small negative or near-zero trends during all the seasons except for DJF. Interestingly, we found that in the interannual variability of the seasonal mean SAM index during all seasons, the spreads in terms of confidence interval for E3SM-AMIP simulation are larger than those for E3SM-HIST simulation (Figures 4a–4d), while the spreads for the trend of the seasonal mean SAM index are similar or reversed (Figure 4e). The reason may be because the variability of the ensemble members is phase-locked to that of the observed SST in AMIP simulations. In addition, we can see the seasonality of the SAM trend for E3SM-AMIP simulation in all seasons is bigger than that of E3SM-HIST simulation. This fact may imply that the SST produced by the coupled model (E3SM-HIST) has weaker variability than the observed SST used in the E3SM-AMIP simulations, as far as the influence on the SAM mode is concerned.

4. Variability and Trend of Position and Strength in SH Surface TAUX

4.1. Variability and Change in Surface TAUX

In Figure 5, we consider variability and trend in position and strength of the annual mean SH surface TAUX for the reanalyses and E3SM simulations over the 36-year period. Table 4 is made to quantify the long-term changes in the kinematic properties for observed and simulated surface TAUX, along with the significance test. In Figure 5a, the positions of zonal mean surface TAUX in the simulations are roughly equivalent to the observed positions, but in the strength of Figure 5d, there is a statistically significant difference that the NCEP-R1 lies outside of 95% confidence interval from the simulated ensemble mean variability over the period between 1981 and 1994. Both ERA-Int and NCEP-R1 show an insignificantly negative trend in the
Figure 6. Variability and trend in position of the seasonal mean surface TAUX over the Southern Ocean for the reanalyses and E3SM simulations. The lines indicate the 5-year running average. The shaded areas envelop the 95% confidence intervals about the E3SM-HIST (red) and E3SM-AMIP (blue) ensemble mean simulations. Trends in the seasonal mean surface TAUX are shown at the bottom panel. The error bars show the 95% confidence interval of the trends for the E3SM-HIST (red) and E3SM-AMIP (blue) ensemble means.

position of the annual mean surface TAUX (Figure 5c and Table 4). Note that a negative trend in the position means a poleward shift. The E3SM simulations also show a decreasing trend in the position of the annual mean surface TAUX. In contrast, the E3SM-4xCO2 simulation has a positive trend (0.44° latitude per decade) in the position (Figure 5c and Table 4). In the strength of the annual mean surface TAUX, two reanalyses and E3SM-HIST and AMIP simulations exhibit positive trends. The E3SM-4xCO2 simulation shows a negative strength trend that is in companion with the equatorward shift of the position. However, the E3SM-1pctCO2 simulation has an insignificantly negative trend in the strength of the annual mean surface TAUX. The magnitude of trend in the strength of the annual mean surface TAUX from the ERA-Int is smaller, unlike the trends of the annual mean SAM index, than that from the NCEP-R1. The E3SM-HIST simulation has statistically significant trends at the 95% confidence level not only in the annual mean SAM index but also in position and strength of annual mean surface TAUX (Tables 3 and 4). As mentioned by previous studies (Swart & Fyfe, 2012; Swart et al., 2015), from the relationship of the changes between the annual mean SH surface TAUX and SAM index obtained by the observed and E3SM simulated data sets, it can be seen that a poleward (equatorward) shift and strengthening (weakening) in trend of the SH surface TAUX are very close to the positive (negative) trend in the SAM index, though it is difficult to find the relationship in the E3SM-1pctCO2 simulation.

Figures 6 and 7 indicate the time evolution and change in position and strength of the seasonal mean surface TAUX over the 35-year period. In the austral winter (JJA) the enveloped area of 95% confidence interval in the two kinematic properties of the seasonal surface TAUX from both E3SM-HIST and AMIP simulations is considerably wider when compared with other seasons. During DJF, the E3SM-AMIP simulations show the positively significant correlation in position (0.58 and 0.52) and strength (0.57 and 0.61) of surface TAUX against both ERA-Int and NCEP-R1 reanalysis data sets, but correlation coefficients of two kinematic properties in MAM do not exhibit any significant values in E3SM-AMIP simulation. The seasonal mean trends in position of surface TAUX from NCEP-R1 reanalysis data set are insignificant during all seasons, while the trends of the observed strength show significant values in all seasons, except for in JJA (Table 4). The
observed trends in strength exhibit much clearer seasonality than those in position. In the position of the SH surface TAUX, the E3SM simulations in MAM mean trends tend to have smaller magnitude relative to both reanalyses (Figure 6e). The position trends of the two historical simulations (HIST and AMIP) in DJF are similar to those seen in the observations (Figure 6e). For the strength, the E3SM simulated trends are substantially smaller than those from ERA-Int and NCEP-R1 in all seasons (except for ERA-Int in JJA) as well as in the annual mean (Figures 5f and 7e and Table 4). The two reanalyses show a positive trend in the strength of the annual and all seasonal mean surface TAUX, but only E3SM-HIST, of all simulations, exhibit the same positive trend as the observed products.

4.2. Climatology of the Position and Strength in Surface TAUX

In a validation of the climatology in the SH zonal wind simulated by the CMIP3 and CMIP5 models, many researchers (Bracegirdle et al., 2013; Fyfe & Saenko, 2006; Russell et al., 2006; Swart & Fyfe, 2012) show that the simulated climatological zonal winds are on average weaker in strength and equatorward biased in position compared to observations. In this section, to examine the kinematic properties of climatological surface TAUX over the 36-year period is computed by longitude for two reanalyses and four E3SM simulations (Figures 8a and 8c) and zonal mean of climatological position and strength is also calculated (Figures 8b and 8d and Table 5). The climatological zonal mean position of surface TAUX in ERA-Int and NCEP-R1 is 52.54° S and 52.77° S, respectively, almost consistent with Swart and Fyfe (2012). Both E3SM-HIST and AMIP simulations indicate slightly equatorward zonal mean position (52.39° S and 52.41° S in each) compared to the reanalyses. Climatological zonal mean from the two CO2 forcing simulations have relatively poleward position, 52.9° S and 53.02° S for E3SM-1pctCO2 and 4xCO2 (Table 5). Compared to the climatological position for the CMIP3 and CMIP5 climate models in Swart and Fyfe (2012), the E3SM-HIST simulation represents an improvement with the position more consistent with that derived from the reanalysis, although this study did not consider the surface TAUX on the land. The climatological poleward position of surface TAUX from the two CO2 simulations mainly occurs in the vicinity of the central Indian (50–120° E) and Atlantic Ocean (60–20° W). The climatological zonal mean strength of the SH surface TAUX from the CO2 simulations (0.232 Pa in 1pctCO2 and 0.227 Pa in 4xCO2) are slightly stronger than the E3SM-HIST (0.210 Pa) and
Table 4
Trends in Position and Strength of the Annual and Seasonal Mean Surface TAUX from Two Reanalyses and Four E3SM Simulations

| Position (degree latitude per decade) | Trend (ANN) | Trend (MAM) | Trend (JJA) | Trend (SON) | Trend (DJF) |
|--------------------------------------|-------------|-------------|-------------|-------------|-------------|
| ERA-Int                               | −0.21       | −0.472      | 0.028       | 0.019       | −0.261      |
| NCEP-R1                               | −0.28       | −0.331      | −0.482      | −0.043      | −0.251      |
| E3SM-HIST                             | −0.17       | 0.067       | 0.096       | −0.415      | −0.363*     |
| E3SM-AMIP                             | −0.17       | 0.056       | −0.062      | −0.395      | −0.260      |
| E3SM-1pctCO2                          | −0.04       | −0.071      | −0.077      | 0.033       | −0.368      |
| E3SM-4xCO2                            | 0.44        | −0.014      | 0.873       | 0.775       | 0.224       |
| Strength (Pa per decade)              |             |             |             |             |             |
| ERA-Int                               | 0.0054*     | 0.0087*     | 0.0005      | 0.0064      | 0.0076*     |
| NCEP-R1                               | 0.0105*     | 0.0135*     | 0.0065      | 0.0121*     | 0.0136*     |
| E3SM-HIST                             | 0.0037*     | 0.0016      | 0.0048*     | 0.0039      | 0.0033*     |
| E3SM-AMIP                             | 0.0016      | 0.0020      | −0.0014     | 0.0049      | 0.0012      |
| E3SM-1pctCO2                          | −0.0012     | 0.0008      | 0.0025      | −0.0052     | −0.0010     |
| E3SM-4xCO2                            | −0.0039     | 0.0015      | −0.0041     | −0.0071     | −0.0038*    |

Note. Asterisk (*) marks indicate statistical significance at the 95% confidence level in the Student two-tailed t-test.

E3SM-AMIP (0.219 Pa) simulations. These climatological zonal mean strengths for the CO2 simulations are especially predominant over the eastern Indian (100–160°E) and central Pacific (160–100°W) Ocean. The E3SM-HIST (0.210 Pa) shows a weaker climatological zonal mean strength, which has a distinctly lower surface TAUX over the western Pacific (150°E to 140°W) Ocean, compared with two reanalyses.

Figures 9 and 10 show the climatological position and strength by longitude of the seasonal surface TAUX for the observations and simulations. During the austral winter (JJA), the climatological position of the maximum surface TAUX by longitude shows the larger variability and wider ensemble spread than other seasons, and interestingly, there is a sharp poleward movement in the climatological position of surface TAUX over the region of 100°E to 180° (Figure 9). We can also find a sharp decrease in the longitudinal change of the JJA climatological strength (Figure 10). In MAM, both E3SM-HIST and AMIP simulations are located in a slightly poleward position relative to both ERA-Int and NCEP-R1, while the climatological zonal mean positions of surface TAUX from two HIST and AMIP simulations during SON and DJF shift relatively equatorward compared to the two reanalyses (Figure 9e and Table 5). The two reanalysis data sets show a more equatorward position and weaker strength in DJF relative to other seasons. All E3SM simulations, except for E3SM-4xCO2, also have a similar seasonal feature as shown in the reanalyses. The CO2 forcing simulations show slightly higher strength, which is commonly predominant over the eastern Indian Ocean, relative to E3SM-HIST and AMIP simulations during all seasons except for DJF (Figure 10 and Table 5). During JJA and SON, the E3SM-HIST simulation has the lowest climatological zonal mean strength compared to other simulations and reanalyses. This may result from lower climatological strength near the western Pacific Ocean.

5. Relationship Between the SAM Index and Surface TAUX

To compare the relationship between the variability in the SAM index and the kinematic properties (latitude position and strength) of the SH zonal mean surface TAUX for annual mean of 36 years, we use scatter diagrams along with the calculated correlation coefficients and slopes of the regression lines for reanalyses and E3SM simulations (Figure 11). The variability in the annual mean SAM index is significantly correlated with the variability in two kinematic properties of SH surface TAUX from reanalyses and E3SM simulations. The relationship between the strength of surface TAUX and the SAM index is positively linear by which an increasing of the SAM index is related to a strengthening of surface TAUX strength, while the variability in the position of surface TAUX is associated with the SAM index in that a poleward movement in surface TAUX position is accompanied by a strengthening of the SAM index. This is consistent with the
Figure 8. Climatological (a) position and (c) strength by longitude of the annual mean surface TAUX over the Southern Ocean for the reanalyses and E3SM simulations and (b, d) their zonal mean. The shaded areas and error bars represent the 95% confidence intervals about the E3SM-HIST (red) and E3SM-AMIP (blue) ensemble means simulation. Note differences in vertical axis extent.

Table 5
Zonal Mean of Climatological Position and Strength of the Annual and Seasonal Mean Surface TAUX From Two Reanalyses and Four E3SM Simulations

|          | ANN   | MAM   | JJA   | SON   | DJF   |
|----------|-------|-------|-------|-------|-------|
| Position (degree latitude) |       |       |       |       |       |
| ERA-Int  | −52.54| −52.63| −52.47| −52.84| −52.09|
| NCEP-R1  | −52.77| −52.89| −52.65| −52.31| −52.07|
| E3SM-HIST| −52.39| −53.13| −52.51| −52.50| −51.42|
| E3SM-AMIP| −52.41| −53.06| −52.68| −52.60| −51.26|
| E3SM-1pctCO2| −52.90| −54.02| −52.58| −52.72| −52.33|
| E3SM-4xCO2| −53.02| −54.52| −52.28| −52.38| −52.96|
| Strength (Pa) |     |       |       |       |       |
| ERA-Int  | 0.219 | 0.221 | 0.237 | 0.221 | 0.197 |
| NCEP-R1  | 0.212 | 0.214 | 0.230 | 0.215 | 0.189 |
| E3SM-HIST| 0.210 | 0.225 | 0.217 | 0.205 | 0.193 |
| E3SM-AMIP| 0.219 | 0.228 | 0.236 | 0.216 | 0.198 |
| E3SM-1pctCO2| 0.232| 0.249 | 0.248 | 0.234 | 0.199 |
| E3SM-4xCO2| 0.227| 0.246 | 0.244 | 0.225 | 0.195 |

The relationship between the SAM index and the kinematic properties of the surface westerly wind jet in Swart et al. (2015). The magnitude of correlation coefficients between the surface TAUX strength and SAM in the reanalyses and E3SM-HIST and AMIP simulations is higher than those between the surface TAUX position and SAM, but the CO₂ simulations show the higher magnitude of correlation coefficients in the relationship between position and SAM index. The slope between surface TAUX strength (or position) and SAM index for NCEP-R1 reanalysis data set is greater than those for model simulations. In the relationship between surface TAUX strength and SAM index for the E3SM simulations, the CO₂ simulations show more gentle
Figure 9. Climatological (a–d) position by longitude of the seasonal mean surface TAUX over the Southern Ocean for the reanalyses and E3SM simulations and (e) zonal mean of climatological position. The shaded areas and error bars represent the 95% confidence intervals about the E3SM-HIST (red) and E3SM-AMIP (blue) ensemble means simulation.

slope values than E3SM-HIST and AMIP simulations, while the CO2 simulations have steeper slopes than the other simulations in the relationship between surface TAUX position and SAM index.

We have also investigated the relationship between the seasonal mean SAM index and kinematic properties in the seasonal mean surface TAUX. Figures 12 and 13 show the scatter diagrams for JJA and DJF. The relationship for other seasons can be seen in Figure S3. The positions of surface TAUX related to the variability of the SAM index for the reanalyses and the simulations show a wider (narrower) fluctuation in JJA (DJF) on average than in all other seasons. In the relationship between the strength in surface TAUX and variability of SAM index for observations and simulations, the fluctuation features similar to those of the surface TAUX position also appear. The correlation coefficients between the surface TAUX strength (position) and SAM index for two reanalyses during JJA (DJF) have significantly positive (negative) high values relative to the other seasons. The absolute values of slope between the strength (position) of surface TAUX variability in the reanalyses are largest in JJA. In the E3SM simulations, it is difficult to find such features by season. In MAM, the positions of surface TAUX related to SAM variability for E3SM-AMIP simulation show the lowest absolute values of the slopes (Figure S3). In DJF, the lowest slopes between strength of surface TAUX and SAM index appear in all E3SM simulations except for 1pctCO2 simulation having the lowest value (0.0011 Pa) in JJA.

6. Summary and Conclusion

Here we study the spatial pattern and temporal variability of the SAM, which is the main mode of atmospheric variability in the SH extratropical regions and its relationship with surface zonal winds. We assess the ability of two ensembles of E3SM simulations, E3SM-HIST and AMIP, to reproduce the SAM characteristics compared to observations over the satellite era. The variability and change of the SAM in the two CO2 experiments (E3SM-1pctCO2 and 4xCO2) are also analyzed to show the model sensitivity in response to different types of increasing CO2 forcings. All E3SM simulations capture the dominant characteristics of
the SAM in the SH, though there are some differences in the location and intensity of the centers for the meridional dipole structure.

For the annual mean trend for the SAM index, both reanalyses showed a clear shift toward positive values. The E3SM-HIST and AMIP simulations reproduced a statistically significant increasing trend. In contrast, the E3SM-4xCO2 simulation indicated a negative trend, while the SAM index in the E3SM-1pctCO2 simulation showed a positive trend that was not statistically significant. The increasing trend in the annual mean SAM from the E3SM-HIST simulation is located between those seen from two reanalyses. Unlike other simulations, only the E3SM-HIST simulation had the statistically significant positive SAM trend (at the 95% confidence level) in all seasons.

We have examined variability and change in the position and strength of the annual mean SH surface zonal wind stress (TAUX) for the observations and E3SM simulations. In the time evolution of the surface TAUX position, we found that the E3SM simulations are quite similar to observations. Unlike the position, the variability of annual mean surface TAUX strength had some differences in the time evolution. The E3SM-HIST and AMIP simulations showed the negative (positive) trend in the position (strength), similarly to both observations. The E3SM-HIST simulation showed statistically significant trends in the position and strength of annual mean surface TAUX as well as in the annual mean SAM index, though the signs for the trends of position and strength (or position and SAM) are different with one another. In the seasonal strength of surface TAUX, the two reanalyses showed significant trends in MAM and DJF seasons. However, there were no significant trends during all seasons in the position of observed surface TAUX.

For climatological position and strength of annual surface TAUX, the two CO₂ forcing simulations were slightly poleward and stronger than both E3SM-HIST and AMIP, and the E3SM-HIST was relatively equatorward and weaker compared to observations. It was interesting that we can see the longitudinal sharp southward (decreasing) change of climatological position (strength) in the vicinity of the eastern Indian Ocean during austral winter (JJA). In austral summer (DJF), all E3SM simulations, except for E3SM-4xCO2, showed a similar seasonal feature to observations, which is that they have a more equatorward position and weaker strength compared to other seasons.

Figure 10. As in Figure 9 but for climatological strength by longitude of the seasonal mean surface TAUX.
Figure 11. Scatter diagram between the annual mean SAM index and kinematic properties (strength and position) in the annual mean surface TAUX for the reanalyses and E3SM simulations. Temporal correlation coefficients and regression coefficients are given at the upper right and bottom left of the panel, respectively.

In the relationship between the the SAM and kinematic properties of the surface TAUX, it was shown that the variability of the SAM index was closely related to the kinematic properties of the surface TAUX. When the SAM was strengthened (weakened), the surface TAUX strength was increased (decreased) and the surface TAUX position showed poleward (equatorward) movement in the variability for all seasons as well as annual mean.

Many recent studies Swart and Fyfe (2012), Simpkins and Karpechko (2012), and Zheng et al. (2013) found that the SH surface TAUX shows a poleward shift of position and strengthening of intensity, and the SAM index has a positive trend in response to the significant increase of CO₂ forcing. However, unlike their results, the E3SM CO₂ forcing simulations (E3SM-1pctCO2 and 4xCO2) in the present study indicate lacks of a
Figure 12. Scatter diagram between the JJA mean SAM index and kinematic properties (strength and position) in the JJA mean surface TAUX for the reanalyses and E3SM simulations. Temporal correlation coefficients and regression coefficients are given at the upper right and bottom left of the panel, respectively.

trend or even an opposite one in the SAM index and kinematic properties of SH surface TAUX. Possible explanations include the relatively short data period and small ensemble size from a single simulation as well as the data sampling, namely, the selection of the last few decades of the simulation for this study, which does not ensure having the same underlying driver for the trend as in the other studies. Nonetheless, the overall results of SH climate variability in these simulations are a promising indication for the E3SM coupled climate system. In addition, the E3SM-HIST and AMIP simulations covering the historical record provide useful information to better understand the atmospheric variability and ocean circulation in the SH through the model performance and diagnostic evaluation for the SAM and surface TAUX based on indirect/direct comparison with observations.
Figure 13. As in Figure 12 but for DJF season.

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