

DISSERTATION

TWO-WAY INTERACTIONS BETWEEN ANTARCTIC SEA ICE AND THE ATMOSPHERIC
CIRCULATION: MECHANISMS FOR AND IMPLICATIONS OF RECENT SEA-ICE LOSS

Submitted by

Chloe L. Boehm

Department of Atmospheric Science

In partial fulfillment of the requirements

For the Degree of Doctor of Philosophy

Colorado State University

Fort Collins, Colorado

Fall 2025

Doctoral Committee:

Advisor: David W.J. Thompson

James Hurrell

David Randall

Daniel McGrath

Copyright by Chloe L. Boehm 2025

All Rights Reserved

ABSTRACT

TWO-WAY INTERACTIONS BETWEEN ANTARCTIC SEA ICE AND THE ATMOSPHERIC CIRCULATION: MECHANISMS FOR AND IMPLICATIONS OF RECENT SEA-ICE LOSS

In contrast to the Arctic, Antarctic sea ice has experienced both long-term positive and negative trends across the observational record. From the 1980s until 2015, Antarctic sea ice experienced a slight positive trend, while Arctic sea ice experienced a consistent negative trend. These weak but steady increases ended abruptly during the austral summer of 2015, when Antarctic sea-ice extent dropped by roughly 2 million km², setting record negative anomalies in November 2016. This low sea-ice state has persisted since, with new record negative anomalies set in July 2023, which were more than four standard deviations below the 1979–2022 mean. The reasons behind these unprecedented changes and the impacts of this new low sea-ice state on the climate system remain open to debate. This dissertation focuses on providing novel observational insights into the effects of the atmospheric circulation on recent sea-ice variability and vice versa.

In Part 1, we provide insights into the role of the Southern Annular Mode (SAM) in driving variations in Antarctic sea-ice area (SIA). Utilizing a mixture of reanalysis and satellite data, we show that the influence of the SAM on Antarctic sea ice exhibits more pronounced seasonality than that indicated in previous work. At the time of the sea-ice *minimum*, positive anomalies in the SAM — and thus enhanced westerlies over the high latitude Southern Ocean — lead to increased SIA over the following four months. In contrast, at the time of the sea ice *maximum*, positive anomalies in the SAM lead to decreased SIA over the following twelve months. Differences in the persistence of the SAM-SIA relationship from one season to the next lead to an outsized impact of variations in the SAM during the sea-ice maximum on annual-mean SIA. The persistence of SAM-induced sea-ice anomalies following the sea-ice maximum is consistent with both anomalous shortwave radiative feedbacks and heat storage in the upper ocean. It is argued that a notable fraction of the

dramatic losses in annual-mean SIA over the past decade can be traced to unprecedented variations in the SAM during the time of the sea-ice maximum.

In Part 2, we provide insights into the impacts of Antarctic sea-ice decline on regional changes in the atmospheric circulation. We perform a gridpoint-by-gridpoint regression technique on re-analysis and satellite data to create an observational estimate of the impacts of Antarctic sea-ice loss. The results highlight a strong relationship between sea-ice loss and increases in turbulent heat flux, precipitation, cloud fraction, and near-surface temperature and wind speed. The strongest relationships occur during the austral winter season, with upwards of a 50% increase in precipitation and near-surface temperature from one standard deviation of sea-ice loss. We then compare these observational results to two atmosphere-only simulations and a fully-coupled model. The atmosphere-only simulations help establish causality and provide the opportunity to isolate the pathways by which sea-ice loss impacts precipitation. The results indicate that a large portion of the predicted Southern Ocean precipitation changes can be attributed to the effects of sea-ice changes on local variations in the surface heat fluxes. The changes in the heat fluxes influence not only local vertical motion, but also vertical motion downwind of the sea-ice anomalies due to changes in the vertical mixing of free tropospheric winds and thus the horizontal convergence of the surface flow.

ACKNOWLEDGEMENTS

I would first like to thank my advisor, Dave Thompson, for his guidance and mentorship during my PhD. He not only taught me how to conduct research and write papers, but also how to always be curious, and that sometimes the best science questions are found while in the mountains. I would also like to thank the members of my PhD committee: Jim Hurrell, Dave Randall, and Dan McGrath for their insightful suggestions and encouragement throughout this process. I would like to thank Ed Blanchard-Wrigglesworth for his thoughtful collaboration throughout this work and Lantao Sun for his guidance and for answering my many questions related to CESM. Thanks to the members of the Thompson Group, both past and present, Casey, Dhyey, James, Jesse, Jingyuan, Leif, Lina, Luke, Shim, Ying-Ju, and Yumi, for being great co-workers to have science conversations with. I would also like to thank the Atmospheric Science Department staff, including Sarah Tisdale and Heidi Hammon. Many thanks to my friends and family for their endless support throughout my time here. Thanks to my dog, Astrid, for relieving stress and reminding me to spend more time outside. Lastly, thanks to my partner Lilly for always supporting, encouraging, and believing in me, for the many visits to the local coffee shops when I needed a pick-me-up, and for being the best person to adventure in the mountains with.

This work is funded by the National Science Foundation's Climate and Large-Scale Dynamics Program.

TABLE OF CONTENTS

ABSTRACT	ii
ACKNOWLEDGEMENTS	iv
LIST OF FIGURES	vii
Chapter 1	Introduction 1
1.1	Background and Motivation 1
1.2	Causes of Antarctic Sea-Ice Variability and Trends 5
1.3	Impacts of Antarctic Sea-Ice Decline 8
1.4	Outline of Dissertation 10
Chapter 2	Data and Methods 12
2.1	Observationally-Constrained Data 12
2.2	Model Output 15
2.3	Analysis Methods 20
Chapter 3	Interpretation of Recent Antarctic Sea-Ice Loss: The Key Role of the Southern Annular Mode During the Seasonal Sea-Ice Maximum 21
3.1	Introduction 21
3.2	Data and Methods 23
3.2.1	Observationally-Constrained Data 23
3.2.2	Model Output 24
3.2.3	Analysis Methods 24
3.3	Results 25
3.3.1	Seasonality of the influence of the SAM on SH SIA 25
3.3.2	The key role of the SAM During the seasonal sea-ice maximum 38
3.3.3	Reproducibility in a climate model 45
3.4	Discussion 47
Chapter 4	An Observational Analysis of the Impact of Antarctic Sea-Ice Loss on Regional Changes in the Atmospheric Circulation 50
4.1	Introduction 50
4.2	Data and Methods 53
4.2.1	Observationally-Constrained Data 53
4.2.2	Model Output 53
4.2.3	Analysis methods 54
4.3	Results 55
4.3.1	Local relationships in observational data 55
4.3.2	Temperature responses at upper-levels 65
4.3.3	The atmospheric response in sea-ice forced simulations 68
4.3.4	Precipitation impacts from future Antarctic sea-ice loss 77
4.3.5	Local relationships in a high-resolution climate model 79

4.4	Discussion	81
Chapter 5	Conclusions and Future Work	83
5.1	Future Work	85
Bibliography		89
Appendix A	Detrending Sensitivity	105

LIST OF FIGURES

1.1	Seasonal Cycle of Antarctic Sea Ice	2
1.2	Time series of sea-ice area	3
1.3	Map of Antarctica with the boundaries for the five sectors denoted. See text for details.	4
2.1	The monthly seasonal cycle of Antarctic sea-ice area from observations (black line), CESM2 historical simulation (blue line), and CESM-HR historical simulation (red line). The climatological seasonal cycle is taken across the common period of 1979–2005. The seasonal cycle shown for CESM2 and CESM-HR is the ensemble mean.	18
2.2	A time series of monthly Antarctic sea-ice area from 1850–2024. Observational data (black line), from the NSIDC, covers the period from 1979–2024, the CESM2 historical simulation (blue line) covers the period from 1850–2015, and the CESM-HR historical simulation (red line) covers the period from 1920–2005. The thick blue and red lines are the ensemble means, and the shading is the ensemble spread.	19
3.1	Observed monthly-mean values of (a) Antarctic sea-ice area anomalies (SIA) and (b) the Southern Annular Mode (SAM). The time series are deseasonalized but not detrended. Months with record negative SIA anomalies are denoted on (a).	26
3.2	The regression for monthly-mean values of Southern Hemisphere-mean sea-ice area (SIA) regressed onto the standardized values of (a) SIA and (b) the Southern Annular Mode (SAM) index. The months on the y-axis indicate the month used as a basis for the regression; the values on the x-axis indicate the lag with respect to the basis month. For example, the first row in (b) shows SIA in units km^2 at lags indicated on the x-axis regressed onto standardized values of the SAM index during January. All data used in panels (a) and (b) are detrended with respect to the long-term mean climatology. Panel (c) shows the climatological seasonal cycle of Antarctic SIA. Hatching indicates regressions that are statistically significant at the 95% confidence intervals. See text for details.	27
3.3	As in Figure 3.2 but for correlations of SIA with itself and the SAM. Note that positive correlations are shaded blue to be consistent with the regressions in Figure 3.2	28
3.4	Regressions onto standardized September values of the Southern Annular Mode index. (a-d) Sea-ice concentration (SIC) for the indicated months regressed onto standardized September values of the Southern Annular Mode (SAM) index. Vectors in (a) show results for September 10-meter winds. (e-h) As in (a-d) but for clear-sky surface short-wave (SW) fluxes regressed onto standardized September values of the SAM index. (i-l) As in (a-d) but for cloudy surface SW fluxes (SW cloud radiative effects (CRE)) regressed onto standardized September values of the SAM index. Black contours indicate where the climatological-mean monthly mean sea-ice concentration is at least 15%. Data are detrended with respect to the long-term mean climatology. Flux anomalies are positive downward and are based on the period 2000–2024.	30
3.5	As in Figure 3.4, but for regressions onto standardized March values of the SAM index.	32

3.6	Regressions onto standardized September values of the SAM index as a function of lag. Black line: The regression of Southern Hemisphere-mean sea-ice area (SIA) as a function of lag onto standardized September values of the Southern Annular Mode (SAM) index. Grey and blue solid lines: As in the black line, but for shortwave (SW) cloud radiative effects (CRE) and SW clear-sky fluxes, respectively. Grey and blue dashed lines: As in the black line, but for longwave (LW) CRE and clear-sky fluxes, respectively. Red line: As in the black line, but for sea surface temperatures (SST). Amplitudes for all fluxes are given on the right axis; amplitudes for SST anomalies and SIA anomalies are indicated on the left axis. The fluxes and SST anomalies are averaged over regions where the sea-ice concentration anomalies for the corresponding month are negative. All data are detrended with respect to the long-term mean climatology. Fluxes are given over the period 2000–2024. See text for details.	33
3.7	As in Figure 3.6 but fluxes and SST anomalies are averaged over all regions with sea-ice concentration anomalies, not only where anomalies are negative.	33
3.8	As in Figure 3.2a, but for correlations of the SAM with itself	35
3.9	As in Figure 3.4, but for regressions onto standardized July values of the SAM index. .	36
3.10	As in Figure 3.4, but for regressions onto standardized August values of the SAM index.	37
3.11	As in Figure 3.6, but for regressions onto standardized July values of the SAM index. .	38
3.12	As in Figure 3.6, but for regressions onto standardized August values of the SAM index.	39
3.13	Quantifying the seasonal relationships between sea-ice area and the Southern Annular Mode. (a) The regression of annual-mean sea-ice area (SIA) anomalies onto monthly values of the Southern Annular Mode (SAM) index, where the annual means are formed from the 12-month period starting on the month indicated on the x-axis. For example: Results for September indicate September-August (during the following year) mean values of SIA regressed onto September values of the SAM index, etc. (b) Monthly-varying values of monthly SIA anomalies discretized by the value of the SAM index during September (colors). Years with anomalously high or low SIA are denoted on the plot. September SAM indices are standardized and only years with September SAM index values exceeding ± 1 standard deviation are shown. Figure concept inspired by Fig. 4 in Doddridge and Marshall (2017). All data are detrended with respect to the long-term mean climatology.	40
3.14	As in Figure 3.13a, but for the variance in annual-mean SIA anomalies explained by variations in the SAM index during the indicated month. For example: Results for September indicate the correlation squared between September-August (during the following year) mean values of SIA and September values of the SAM index, etc. . . .	41
3.15	As in Figure 3.13b, but with all other years that were not shown in Figure 3.13b shown in light gray lines; i.e., all years where the standardized September SAM was within ± 1 standard deviation.	42
3.16	As in Figure 3.13a, but using the Niño3.4 index obtained from the NOAA Climate Prediction Center.	42

3.17	Time series of inverted and standardized September values of the Southern Annular Mode (SAM) index (gray) and standardized values of sea-ice area (SIA) anomalies as a function of month (black). That is: Each row shows the same September SAM index time series superposed on standardized values of SIA for the indicated months. The SAM index time series is inverted for the purpose of illustration. SIA time series for months January, March, May, and July are shifted by one year so that they align with the SAM index time series during the previous September. The correlation coefficients between each month of SIA and the inverted September SAM are labeled above each time series pair. All data are detrended with respect to the long-term mean climatology. Missing data in the January time series is explained in the Methods section. SIA months shown are chosen at 2-month intervals.	43
3.18	As in Figure 3.17, but for additional months not shown in Figure 3.17. SIA time series for months February, April, June, and August are shifted by one year so they align with the SAM index time series during the previous September. Correlation coefficients between each month of SIA and the inverted September SAM are labeled above each time series pair.	44
3.19	As in Figure 3.2b and Figure 3.13a, but for data limited to the period 1979–2015. . . .	45
3.20	As in Figure 3.2b but with CESM2 run under CMIP6 historical forcing from 1850–2015. Results are showing the ensemble mean of the 11-member ensemble. Regression coefficients are calculated for each ensemble member before the ensemble mean is calculated.	46
3.21	As in Figure 3.2b but with CESM2 run under CMIP6 historical forcing from 1850–2015. Each panel shows results for a different ensemble member that was part of the 11-member ensemble.	46
3.22	The relationship between sea-ice area and the Southern Annular Mode in CESM2. (a–d) As in Figure 3.2b, but for results based on ensemble mean output from CESM2 for the periods indicated. Results are formed for individual ensemble members and then averaged over all ensembles. All output is detrended over the indicated periods. (e) Time series of September and February sea-ice area (SIA). SIA used in time series is neither detrended nor deseasonalized. Output from 1900–2015 is derived from the historical simulation; output from 2015–2100 is derived from the SSP5-8.5 simulation. See the main text and Methods for details.	48
4.1	Standard deviation of (a–d) sea-ice concentration (SIC), (e–h) turbulent heat flux (THF), (i–l) precipitation rate, and (m–p) cloud fraction monthly anomalies across the observational record for each season. Each column is a different season, (a,e,i,m) is August, September, and October (ASO), (b,f,j,n) is November, December, and January (NDJ), (c,g,k,o) is February, March, and April (FMA), (d,h,l,p) is May, June, and July (MJJ). The black contour on each plot is the climatological sea-ice extent (SIE; i.e. the edge of where sea-ice concentration is at least 15%) for the corresponding season.	56
4.2	Standard deviation of (a–d) 2-meter temperature, (e–h) 10-meter wind speed, (i–l) 500 hPa wind speed monthly anomalies for each season. Each column is a different season, and the black contour is the climatological SIE, structured like Figure 4.1.	57

4.3	Maps of regression coefficients from (a) SIC, (b) THF, (c) precipitation rate, (d) cloud fraction regressed onto standardized inverted SIC. Regressions are computed across all months across the entire observational period.	58
4.4	As in Figure 4.3 but split up by season. (a-d) SIC, (e-h) THF, (i-l) precipitation rate, (m-p) cloud fraction regressed onto standardized inverted SIC. Regressions are computed for each season, with each column showing results from each season.	60
4.5	Correlations between inverted SIC and (a-d) THF, (e-h) precipitation rate, and (i-l) cloud fraction, discretized by season. Each column shows the result from a different season. Stippling indicates statistically significant correlations at the 95% confidence interval.	62
4.6	As in Figure 4.4 but for regressions of 2-meter temperature, 10-meter wind speed, and 500 hPa wind speed onto standardized inverted SIC loss.	63
4.7	As in Figure 4.5 but for (a-d) 2-meter temperature, (e-h) 10-meter wind speed, (i-l) 500 hPa wind speed.	64
4.8	Regression of August, September, and October seasonal mean regression of (a) 500 hPa and (b) 850 hPa temperature onto standardized inverted SIC. (c,d) Vertical profile of area-averaged regressions of temperature onto standardized inverted SIC. Regions that are area-averaged are indicated with black boxes in (a), with arrows pointing to the corresponding vertical profile. Latitude and longitude bounds of the area averages are indicated in the titles of (c) and (d).	66
4.9	Climatological standard deviation of (a) 500 hPa and (b) 850 hPa temperature during the August, September, and October season.	67
4.10	As in Figure 4.4 but with transient SIC simulations. Regressions are calculated for each ensemble member, and then an ensemble mean is calculated, which is shown here.	70
4.11	As in Figure 4.6 but with the transient SIC simulations. Regressions are calculated for each ensemble member, and then an ensemble mean is calculated, which is shown here.	71
4.12	Ensemble mean August, September, October season regressions of (a) 500 hPa and (b) 850 hPa temperature onto standardized inverted SIC in the transient SIC simulations. Regressions are calculated for each ensemble member before calculating the ensemble mean.	72
4.13	The seasonal difference in (a-d) SIC, (e-h) THF, (i-l) precipitation rate, and (m-p) cloud fraction between the future Antarctic SIC simulation and the preindustrial Antarctic SIC simulation from the PAMIP experiments. As in Figure 4.4 each column is a different season.	74
4.14	Changes in (a-d) SIC, (e-h) 2-meter temperature, (i-l) 10-meter wind speed, and (m-p) 500 hPa wind speed between the future Antarctic SIC experiment and the preindustrial Antarctic SIC experiment from the PAMIP experiments.	76
4.15	Seasonal decomposition of precipitation impacts into local and remote relationships with sea-ice loss. (a-d) Total precipitation difference between the future Antarctic SIC simulation and the preindustrial Antarctic SIC simulation. (e-h) The regression of precipitation onto sea-ice loss from the transient SIC simulations multiplied by sea-ice change between the future Antarctic SIC simulation and the preindustrial Antarctic SIC simulation. (i-l) The residual of the fit calculated by subtracting row two from row one. Each column is the results for each season.	78

4.16	As in Figure 4.4 but with CESM-HR historical simulation. These are ensemble mean results. Regressions are calculated for each ensemble member and then the ensemble mean is calculated.	80
A.1	As in Figure 3.2b but with different methods of detrending. (a) SIA and SAM time series linearly detrended with a base period of 1979–2015 prior to analysis and (b) SIA and SAM time series not linearly detrended prior to analysis.	105

Chapter 1

Introduction

1.1 Background and Motivation

Sea ice is an integral part of the climate system. It helps regulate the exchange of heat and moisture between the atmosphere and the ocean by 1) insulating the relatively warm ocean from the cold atmosphere in the winter and 2) allowing the exchange of heat and moisture in areas of cracks or leads (e.g. Holland and Bitz 2003; Parkinson 2004; Josey et al. 2024; Landrum and DuVivier 2024 and references therein). Thus, the amount of sea-ice coverage is directly related to how much heat and moisture are lost to the atmosphere, influencing atmospheric conditions (e.g., Deser et al. 2000; Ayres et al. 2022; Josey et al. 2024; Landrum and DuVivier 2024, and references therein). Sea ice can also impact the ocean circulation by increasing the salinity when sea ice forms and increasing the freshwater content when sea ice melts (e.g., Lubin and Massom 2006; Haumann et al. 2016; Pellichero et al. 2018; Rintoul 2018 and references therein). Increased salinity of ocean water increases its density, causing the water to sink to deeper levels of the ocean and contribute to Antarctic Bottom Water. Vice versa, melting sea ice freshens the surrounding water, decreasing its density and converting deep waters to intermediate waters. These processes then directly impact the strength of the overturning circulation (e.g., Haumann et al. 2016; Komuro and Hasumi 2003; Rintoul 2018 and references therein).

In addition to impacts on the atmospheric and oceanic circulations, sea ice impacts other aspects of the local climate and ecosystems. Sea ice drives primary production and is considered a valuable energy source for polar marine food webs (e.g., Koch et al. 2023). Sea ice melt has important implications for enhanced ice shelf melt, which can lead to global sea level rise (e.g., Meredith et al. 2019). Recently, negative anomalies have also been shown to have impacts on populations of wildlife in polar regions (Sahanatian and Derocher 2012; Fretwell et al. 2023) and on hunting/harvesting for Indigenous communities (Hauser et al. 2021). Given the integral role

of sea ice in the climate system, it is essential to understand both the drivers and consequences of sea-ice change.

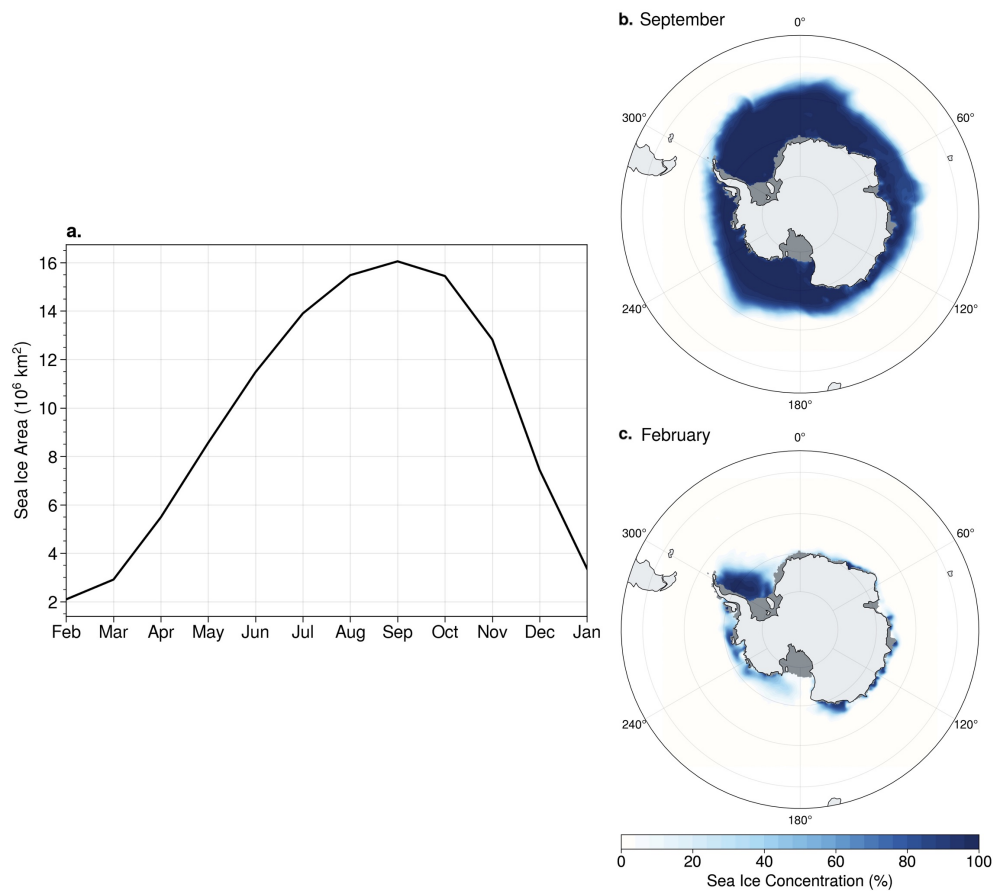


Figure 1.1: (a.) The climatological seasonal cycle of Antarctic sea-ice area across the observational period. Maps of (b.) September and (c.) February climatological sea-ice concentration. Gray shading indicates ice shelf extents. Data source NSIDC.

Despite both the Arctic and Antarctic regions having many similar climatic features, there are some important differences, especially when related to sea ice. Sea ice has a large seasonal cycle, but it is much larger in the Antarctic compared to the Arctic. In the Arctic, the annual maximum occurs in March and the annual minimum occurs in September, with sea-ice extent (SIE), the total area covered by at least 15% sea ice, varying by roughly 9 million km^2 across the year (Roach and Meier 2024). In the Antarctic, the annual maximum occurs in September, and the annual minimum occurs in February, with an annual variation of SIE of 16 million km^2 (or an annual

variation of sea-ice area (SIA), the total area covered by sea ice, of 14 million km² (Figure 1.1)). The seasonal variation of Antarctic sea ice is one of the largest seasonal changes in the Earth's system (Lieser et al. 2014). This difference in seasonality can be partially understood from the fact that Arctic sea ice is bounded by the surrounding continents, whereas Antarctic sea ice is surrounded by the vast Southern Ocean, providing the opportunity for the sea-ice pack to expand. During the annual Antarctic sea-ice minimum, very little sea ice remains, and what does remain is close to the continent (Figure 1.1). This means that much of Antarctic sea ice is first-year sea ice around 1–2 m thick, in contrast to the Arctic, where there is a substantial amount of multi-year sea ice, with thicknesses ranging from 2–3 m (Bocquet et al. 2024).

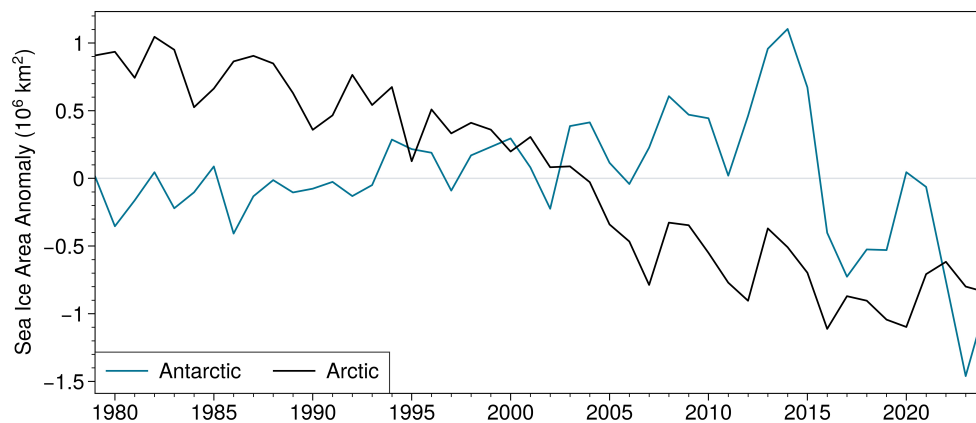


Figure 1.2: Observed annual-mean values of sea-ice area anomalies for the Antarctic and the Arctic. Data source NSIDC.

Arctic and Antarctic sea ice have also experienced very different trends across the observational record (Figure 1.2). Arctic sea ice has been declining across much of the observational record, while Antarctic SIE had a slight positive trend until 2015 (Parkinson 2019; Roach and Meier 2024). Since 2015, Antarctic sea ice has experienced unprecedented decline, with rates of loss exceeding those in the Arctic and setting record negative anomalies in November 2016 and July 2023 (Parkinson 2019; Raphael and Handcock 2022; Turner et al. 2022; Liu et al. 2023; Roach and Meier 2024). In total, the annual mean extent of Antarctic sea ice decreased by approximately 2.5 million km² between 2015 and 2023. For context, Arctic sea-ice extent decreased by roughly

0.2 million square kilometers over the same period (Roach and Meier 2024). Antarctic sea ice has remained anomalously low since 2023, with annual mean sea ice in 2024 being the second lowest on record (Figure 1.2; Roach and Meier 2025). Despite these dramatic changes in Antarctic sea ice, there is still no consensus on what the causes or potential implications may be.

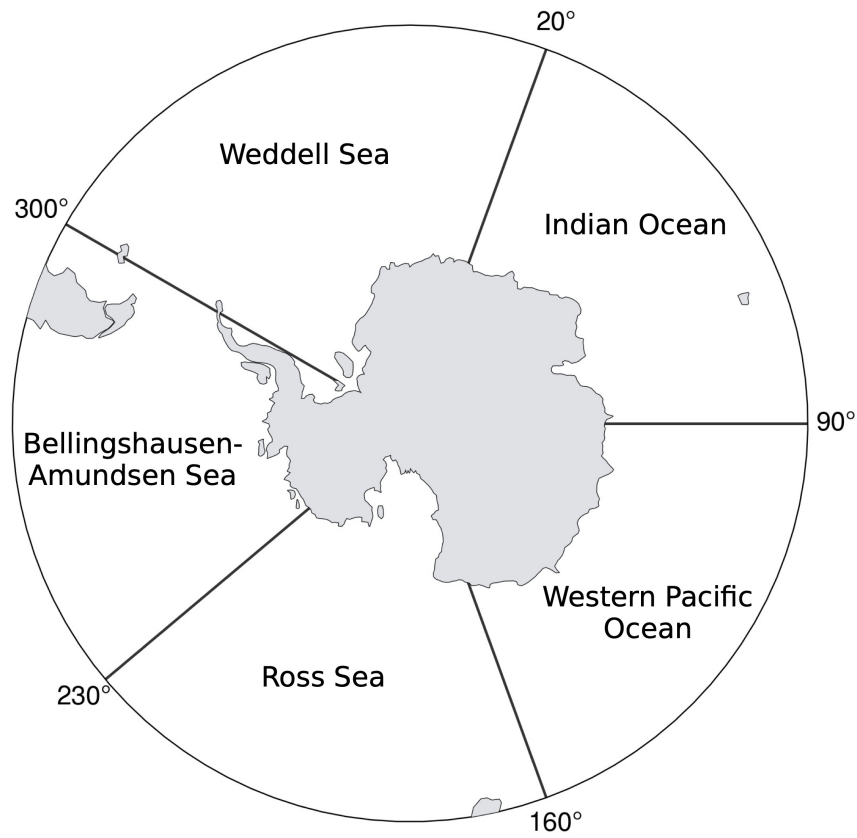


Figure 1.3: Map of Antarctica with the boundaries for the five sectors denoted. See text for details.

Given the remaining open questions regarding Antarctic sea ice, this dissertation will be focused on the Antarctic. We define the regions of Antarctic sea ice based on traditional definitions based on ocean basins (Parkinson and Cavalieri 2012; Maksym and Stammerjohn 2025). There have been other definitions of sea-ice sectors proposed, such as based on characteristic variability (Raphael and Hobbs 2014), but the following sector boundaries are the most common. The region of sea-ice coverage is broken into five sectors, the Weddell Sea (60°W–20°E), the Indian Ocean (20–90°E), the Western Pacific Ocean (90–160°E), the Ross Sea (160°E–130°W), and the

Bellingshausen-Amundsen Sea (130–60°W; see Figure 1.3). These sector definitions will be used throughout this dissertation when referencing regions around Antarctica. We will now provide a review of past literature related to the causes and implications of Antarctic sea-ice variability and trends.

1.2 Causes of Antarctic Sea-Ice Variability and Trends

Various physical factors have been linked to both the weak increases in Antarctic sea ice between 1980–2015 and the dramatic losses thereafter (e.g., see discussion in Blanchard-Wrigglesworth et al. 2022). The sea-ice increases have been linked to tropical phenomena such as the El Niño–Southern Oscillation and the Interdecadal Pacific Oscillation (IPO; Ciasto et al. 2015; Hobbs et al. 2015; Meehl et al. 2016; Li et al. 2021; Chung et al. 2022; Bonan et al. 2024). It has been shown that an El Niño event leads to a weakened Amundsen Sea Low (ASL), and that the associated anomalous anticyclonic atmospheric circulation can alter the SIE in the Amundsen, Bellingshausen, and Weddell Seas (Li et al. 2021). Meehl et al. (2016) attributed some of the pre-2015 sea-ice growth to the phase of the IPO, connecting the transition from the positive to negative phase of the IPO with a deepening of the ASL and a resulting expansion of sea ice.

Another proposed mechanism behind sea-ice expansion is the freshening of the Southern Ocean via ice shelf melt and changes in precipitation/evaporation (Fyfe et al. 2012; Pauling et al. 2016; Purich et al. 2018; Sadai et al. 2020; Rye et al. 2020; Dong et al. 2022). These studies suggested that increased freshwater input from ice shelf melt caused sea-ice expansion by increasing the subsurface stratification and preventing warmer, deeper water from interacting with the surface. In particular, Fyfe et al. (2012) argued that changes in precipitation and evaporation increased freshwater input, causing the observed sea-ice expansion.

One additional avenue that has been explored stems from trying to understand why models are unable to capture the observed positive sea-ice trend. Past studies have ‘nudged’ models to observational conditions to determine which factors were most important for capturing the recent trends. Blanchard-Wrigglesworth et al. (2021) and Zhang et al. (2021) nudged winds and sea-surface tem-

peratures (SSTs) to observed values, and found that, in particular, the accurate representation of Southern Ocean cooling was key to replicating the observed sea-ice trend. Sun and Eisenman (2021) modified the simulated sea ice velocity field to observed sea-ice motion and found that the model was now able to reproduce the observed sea-ice expansion.

Sea-ice expansion has also been linked to changes in the surface flow connected to ozone depletion (Turner et al. 2009; Doddridge and Marshall 2017). The ozone depletion hypothesis, however, has received some debate with certain studies finding that ozone depletion causes substantial sea ice melting (Bitz and Polvani 2012) or that it has had a relatively small impact on sea ice (see review by Previdi and Polvani 2014). Ferreira et al. (2015) introduced a "two-timescale mechanism" that could help reconcile these results involving the Southern Annular Mode (SAM). The SAM is characterized by variations in the strength of the westerly winds over the Southern Ocean (e.g., Thompson and Wallace 2000). During the positive phase of the SAM, the surface westerly winds are enhanced around 60°S and weakened further north. Ferreira et al. (2015) suggested that there was a fast response where a positive SAM anomaly and associated enhanced westerlies led to increased equatorward Ekman transport at the ocean surface. This would increase sea ice cover due to direct wind forcing and colder SSTs. They then suggested there was a longer timescale where the deeper ocean circulation responded to changes in the wind forcing, leading to increased upwelling of deeper, warmer ocean waters. Several studies confirmed this two-timescale response in models, but there was disagreement on what the two timescales were (Holland et al. 2017; Kostov et al. 2017). There was also continued disagreement amongst models as to whether this fast cooling phase and slow warming phase could explain the observed positive trend (Polvani et al. 2021).

Finally, the positive sea-ice trends have been linked to variations in the atmospheric flow over the Southern Ocean, such as the SAM (Hall and Visbeck 2002; Stammerjohn et al. 2008; Simpkins et al. 2012; Raphael and Hobbs 2014; Kostov et al. 2017; Schemm 2018; Roach et al. 2023). As mentioned previously, a positive SAM results in enhanced westerly winds. This induces Ekman drift, which, through mass continuity, results in anomalous upwelling along the periphery of the

Antarctic continent and downwelling around 45°S, resulting in anomalous flow away from the Antarctic continent (Hall and Visbeck 2002). These studies argued that this anomalous flow led to sea-ice advection north, increasing sea-ice coverage, and that the observed positive trend in the SAM could explain the positive trend in sea ice (Fogt and Marshall 2020). Notably, much of this work was focused on changes in annual-mean or just the austral summer season because that has been the season of the largest positive trend in the SAM (Marshall 2003; Thompson et al. 2011; Polvani et al. 2011; Fogt and Marshall 2020).

The recent declines have also been linked to a wide range of atmospheric and oceanic processes. Numerous studies have attributed the declines to atmospheric processes, based on the understanding of atmospheric-sea ice linkages developed in work focused on the previous sea-ice expansion. Specifically, possible factors that have been investigated include a persistent zonal wave number three pattern that enhanced meridional flow (Schlosser et al. 2018; Purich and England 2019), a record negative IOD index that induced positive SST anomalies and enhanced convection (Wang et al. 2019), and negative values of the SAM (Doddridge and Marshall 2017; Turner et al. 2017; Stuecker et al. 2017; Schlosser et al. 2018; Turner et al. 2022; Yadav et al. 2022; Zhang et al. 2022).

While many of these papers have focused on concurrent relationships or lagged relationships of lag greater than a year, a couple have looked at lagged relationships of a few months. Turner et al. (2022) noted that the mean sea-level pressure anomalies during 2021/2022 were characteristic of the positive phase of the SAM, suggesting that less sea ice during the minimum extent might result from a positive SAM during the previous October or November. Yadav et al. (2022) found that the positive state of the SAM in September 2021 deepened the ASL, resulting in increased spring sea-ice retreat and low sea ice the following summer. Holland et al. (2018) detailed the lagged relationship between the ASL and sea-ice variability, noting that the relationship is strongest at a lag of a few months and can persist for up to 8 months. They also note a seasonal reemergence of ASL-related sea ice increases, in particular for October and November ASL variations. These

studies indicate that lagged relationships are important to consider, but that there is still more work to be done to fully understand these relationships, especially outside the summer season.

Other studies have concluded that while variations in the atmospheric flow may have initiated some negative sea-ice anomalies, it was changes in upper-ocean heat content that were responsible for the continued low sea-ice state (Meehl et al. 2019; Zhang et al. 2022; Purich and Doddridge 2023; Jena et al. 2024; Espinosa et al. 2024; Kusahara and Tatebe 2025). Espinosa et al. (2024) specifically concluded that $\sim 70\%$ of the sea-ice anomalies in austral winter 2023 were driven by warm Southern Ocean conditions, and the remaining $\sim 30\%$ was attributable to the atmospheric circulation. Purich and Doddridge (2023) concluded that previously important relationships, such as the connection between sea ice and the SAM, may no longer dominate changes in sea-ice variability, with instead an increasing role of subsurface ocean warming. In addition to the role of the ocean, attention has been given to how regional circulation anomalies and polar cyclones might have been more important than the larger atmospheric modes for explaining the recent anomalies (Jena et al. 2024). The coupled atmosphere-ocean impact on Antarctic sea ice multidecadal variability has recently been highlighted, with a particular focus on the impact of the SAM resulting in increased deep convection (Morioka et al. 2024). While there is still no consensus on what mechanisms caused the recent sea-ice anomalies, there is a consensus that both the atmosphere and ocean have played an important role (Zhang et al. 2022; Hobbs et al. 2024).

1.3 Impacts of Antarctic Sea-Ice Decline

As demonstrated in the previous section, a significant body of work has been dedicated to understanding the causes behind the recent Antarctic sea-ice decline, with fewer studies focused on the consequences. This is in contrast to the Arctic, where there is a large body of literature dedicated to understanding the impacts of sea-ice loss on the atmospheric circulation (e.g., Deser et al. 2010; Screen and Simmonds 2010a,b; Blackport and Kushner 2017; Sun et al. 2018; Zappa et al. 2018; Screen and Blackport 2019; Smith et al. 2022). This discrepancy may partially be

because Arctic sea ice has been declining for many decades, while Antarctic sea-ice decline is still relatively recent.

As of now, the few studies focused on impacts from Antarctic sea-ice loss on the climate system are primarily modeling studies. Some of these studies have used atmosphere-only simulations (Menéndez et al. 1999; Kidston et al. 2011; Bader et al. 2013; England et al. 2018; Wang et al. 2020; Rea et al. 2024), while others have used fully coupled models (Raphael et al. 2011; Smith et al. 2017; Ayres et al. 2022; England et al. 2020a,b; Ayres et al. 2022; Hay and Kushner 2024). In the atmosphere-only modeling studies, there has been some disagreement on the strength of the impacts, with Kidston et al. (2011) finding that future Antarctic sea-ice loss has very little impact on the Southern Hemisphere mid-latitude circulation, while other studies have found a significant impact via shifts in the mid-latitude jet and stormtracks (Menéndez et al. 1999; Bader et al. 2013; England et al. 2018). England et al. (2018) compared the atmospheric response from Arctic versus Antarctic sea-ice loss and found that the response to Antarctic sea-ice loss was weaker and more vertically confined than due to Arctic sea-ice loss.

Previous work in the Arctic has shown the importance of atmosphere-ocean coupling for fully recovering the impacts of sea-ice loss, noting that without such coupling, impacts are more latitudinally confined to higher latitudes and lower levels of the atmosphere (Blackport and Kushner 2016; Deser et al. 2015, 2016; Tomas et al. 2016). Studies in the Antarctic have come to similar conclusions (Smith et al. 2017; England et al. 2020a,b; Ayres et al. 2022; Hay and Kushner 2024). Ayres et al. (2022) directly compared the impacts of Antarctic sea ice loss in coupled and uncoupled experiments and showed that experiments with atmosphere-ocean coupling exhibited stronger lower-tropospheric warming and responses extending to the tropics and into the Northern Hemisphere. Some of these coupled studies showed that Antarctic sea-ice loss could even trigger additional Arctic sea-ice loss (England et al. 2020a; Ayres et al. 2022). England et al. (2020a) focused primarily on impacts in the tropics, highlighting that Antarctic sea-ice loss warms the eastern equatorial Pacific and causes an equatorward intensification of the Intertropical Convergence Zone.

In addition to these previous studies focused on tropospheric impacts of Antarctic sea-ice loss, there is a growing body of research that has begun to investigate the potential stratospheric impacts of Antarctic sea-ice loss. Namely, Rea et al. (2024) and Song et al. (2025) found that low Antarctic sea ice can lead to a weaker stratospheric polar vortex, particularly during winter. However, both studies used atmosphere-only simulations, noting that more work should be done with fully coupled models to completely capture the strength of the connections.

Most of the prior research on the impacts of Antarctic sea-ice loss has been completed using models, with only a couple of studies using observationally-constrained datasets such as reanalysis or satellite data. Zhang et al. (2023) used reanalysis data to show the tight coupling between storm tracks and sea-ice concentration (SIC) anomalies, highlighting the ability of negative SIC anomalies to alter the near-surface temperature gradient, which enhances the atmospheric baroclinicity, increases the eddy kinetic energy, and strengthens the storm tracks. Kromer and Trusel (2023) used observationally-constrained data to focus on the impacts of sea ice loss on precipitation over the Antarctic ice sheet. Most recently, Josey et al. (2024) conducted a case study on the record negative sea-ice anomalies during the winter of 2023 and the impacts on the local atmosphere. They showed that large negative sea-ice anomalies during that winter resulted in substantial heat loss from the ocean to the atmosphere, which in turn increased the storminess in the Antarctic sea-ice region.

1.4 Outline of Dissertation

The goal of this dissertation is to provide new insights into the driving mechanisms and potential implications of recent Antarctic sea-ice change. Specifically, this dissertation focuses on two-way interactions between the atmosphere and sea ice: how changes in the atmospheric circulation can impact sea-ice variability and how sea-ice variability can impact the local atmospheric conditions. Results are primarily based on observationally-constrained data, with additional accompanying results from modeling experiments.

Chapter 2 describes the data and methods used throughout this dissertation, as well as insights into potential biases and uncertainties of such datasets. Chapter 3 provides novel observational insights into the influence of the SAM on recent hemispheric-mean Antarctic sea-ice variability. Chapter 4 provides observational analyses of the impacts of Antarctic sea-ice decline on regional changes in the atmospheric circulation. Chapter 5 provides concluding remarks about this dissertation as well as future research directions prompted by this work.

Chapter 2

Data and Methods

2.1 Observationally-Constrained Data

Sea ice concentration data is commonly measured using passive microwave sensors (Comiso et al. 1997). Passive microwave sensors measure the emitted radiance from the surface, which is dependent on physical temperature and surface composition. This measured value is often called the brightness temperature. Ice emits more microwave energy than liquid water, thus after running the observations through an algorithm, these measurements can help determine the fraction of the surface covered in sea ice. A major advantage of these passive microwave sensors is that they can “see” through clouds and can be operated both during the daytime and nighttime, which is important for creating a continuous record of measurements, particularly in polar regions.

Monthly sea-ice concentration (SIC) data used throughout this dissertation are from the National Oceanic and Atmospheric Administration/ National Snow and Ice Data Center (NOAA/NSIDC) Climate Data Record of Passive Microwave Sea Ice Concentration, Version 4 (Meier et al. 2021a) and the Near-Real-Time NOAA/NSIDC Climate Data Record of Passive Microwave Sea Ice Concentration, Version 2 (Meier et al. 2021b), and have a spatial resolution of 25 km x 25 km. The near-real-time sea-ice concentration dataset is used from January 2024–July 2024 to provide a continuous record from January 1979 to July 2024, except for December 1987 and January 1988, where there is missing data due to satellite retrieval issues. Sea-ice concentration is reported as the fraction of each grid cell that is covered by sea ice. This dataset provides a Climate Data Record (CDR) of sea ice concentration, derived from passive microwave data. The algorithm this product uses to translate passive microwave data to sea ice concentration is a combination of two ice concentration estimates from the NASA Team (NT) algorithm (Cavalieri et al. 1984) and the NASA Bootstrap (BT) algorithm (Comiso and Nishio 2008). Both of these algorithms use brightness temperatures across three different channels to determine the concentration of sea ice. The

NT algorithm compares the ratio of brightness temperatures to known ratios corresponding to different surface types. The ratios are different for an ice-free water surface versus an ice-covered surface. The BT algorithm also uses brightness temperature observations, but then uses scatterplot interpolation between known observed values of an open ocean and ice-covered surface.

The CDR algorithm then combines results from the NT and BT algorithms by selecting the higher concentration estimate for each grid cell. This is done to capitalize on the strengths of each algorithm and results in ice concentration estimates that are more accurate than they would be from either algorithm individually (Meier et al. 2021a).

In Chapter 3, monthly mean indices of the Southern Annular Mode (SAM) and the Niño3.4 index are from the NOAA Climate Prediction Center (CPC). The SAM indices are calculated by projecting the 700 mb height anomalies poleward of 20°S onto the leading Empirical Orthogonal Function analysis of 700 mb height, then normalizing by the standard deviation of the monthly index for the 1979–2000 base period (Mo 2000).

We use monthly-mean data from ECMWF Reanalysis v5 (ERA5) throughout this dissertation (Hersbach et al. 2020). ERA5 is a 4D-var global atmospheric reanalysis that covers the period from January 1940 to the present. We use this data starting in 1979, since ERA5 has been shown to be more accurate after the advent of the modern satellite era, especially in the Southern Hemisphere (Bell et al. 2021). ERA5 ingests many in-situ and satellite observations, ranging from 17,000 per day in 1940 to 25 million per day by 2022 (Soci et al. 2024). Thus, although it is inherently still a model, it is constrained by observations, giving the closest approximation to a spatial and temporally continuous observational dataset available. ERA5 has a horizontal resolution of 0.25°x0.25° and 137 vertical levels up to a height of 80 km.

Past work has shown that ERA5 has biases over the Southern Ocean and Antarctica in near-surface temperatures (King et al. 2022; Garza-Girón and Tulacz 2024; Wang et al. 2024) and radiative fluxes (Silber et al. 2019; Wang et al. 2020; Mayer et al. 2021; Mallet et al. 2023). Reanalysis products generally struggle to accurately simulate radiative fluxes over the Southern Ocean, potentially due to the lack of observations (Trenberth and Fasullo 2010) or the

representation of mixed-phase clouds (Silber et al. 2019). Surface temperature and heat flux biases found over areas of sea-ice coverage have been attributed to the fact that ERA5 has a fixed sea-ice thickness of 1.5 meters and does not simulate snow accumulation on top of sea ice (Batrak and Müller 2019). Despite this, past work has shown that turbulent heat fluxes in ERA5 agree well with other reanalysis products, and ERA5 has successfully been used to estimate turbulent heat fluxes resulting from sea-ice loss (Josey et al. 2024).

We use shortwave and longwave radiative flux data in addition to cloud fraction data from the Clouds and the Earth's Radiant Energy System (CERES) Edition 4.2 Energy Balanced and Filled (EBAF) data product (Kato et al. 2018; Loeb et al. 2018) to avoid some of the biases that exist in ERA5. CERES-EBAF is a satellite data product that has monthly data starting in March 2000 and a horizontal resolution of $1^\circ \times 1^\circ$. The CERES product for these variables is used in lieu of ERA5 because of the previously mentioned biases in ERA5 related to radiative fluxes, especially prior to 2000 (Mayer et al. 2021), and because prior work has shown that CERES simulates radiative fluxes more accurately than ERA5 (Loeb et al. 2022). However, radiative fluxes from the CERES product are not without biases. Studies have found that CERES surface shortwave fluxes are larger than observations and longwave fluxes are smaller than observations in certain regions of the Southern Ocean (e.g., Kato et al. 2018; Hinkelmann and Marchand 2020). These studies generally find small biases in the CERES product, which, while important to consider especially for research focused on small regions, do not preclude the use of the CERES product, especially for the work presented in this dissertation.

Finally, the last observational data product we use is observational sea-surface temperature (SST) data from the Hadley Centre Sea Ice and Sea Surface Temperature (HadISST) dataset (Rayner et al. 2003). HadISST provides a monthly globally complete sea ice and SST dataset on a $1^\circ \times 1^\circ$ grid starting in 1871. We use the dataset starting in 1979 to align with the availability of other datasets used in this work. Observations are taken from ship tracks, buoys, and satellite data, and then interpolated to create a globally complete data product. The HadISST dataset sets SST values to -1.8°C for areas with $> 90\%$ sea-ice concentration, and to NaN for areas with

100% sea-ice concentration. Since there are still relatively few in-situ observations in the Southern Ocean, past work has suggested that there may be a small cold bias there (Rayner et al. 2003)

2.2 Model Output

In addition to observationally-constrained data, we use model output from different experiments run on the Community Earth System Model (CESM; Danabasoglu et al. 2020). CESM is a coupled Earth System Model consisting of atmosphere, ocean, sea ice, land, land-ice, river, and wave models that exchange fluxes and states with a coupler. It was created through collaboration between scientists, students, and software engineers at the National Center for Atmospheric Research and other universities/research institutes (Danabasoglu et al. 2020).

In Chapter 3, we use version 2 of CESM (CESM2) run with Coupled Model Intercomparison Project Phase 6 (CMIP6) historical and SSP5-8.5 simulations. The SSP5-8.5 scenario is the fossil-fuel development scenario with an additional radiative forcing of 8.5 W/m^2 by 2100 and represents the scenario with very high greenhouse gas emissions (Riahi et al. 2017). The historical period simulations (covering the period 1850–2025) have 11 ensemble members, and the SSP5-8.5 simulations (covering the period 2015–2100) have three ensemble members. We use all 11 members when analyzing output from the historical simulations, as well as the three common ensemble members from the historical and SSP5-8.5 simulations to create a continuous record from 1900–2100. Simulations used in this chapter from CESM2 have a nominal horizontal resolution of 1.25° longitude $\times$ 0.9° latitude and are run using the Community Atmosphere Model Version 6 (CAM6), which has 32 vertical levels and a model top of 2.26 hPa.

Danabasoglu et al. (2020) evaluated CESM2 against the previous CESM version (CESM1) and observations. One of the main concerns in CESM2 was unrealistically extensive sea ice in the Labrador Sea region. This unrealistic representation of sea-ice cover is limited to the Northern Hemisphere, with Antarctic sea ice showing promising agreement with observations. CESM2 was shown to have improved representation of tropical wet biases, a reduction in reflective biases of

clouds in the tropics, and a better representation of the surface mass balance of the Greenland and Antarctic ice sheets, among others (Danabasoglu et al. 2020).

In Chapter 4, we use model output from CESM, but we use output from two atmosphere-only experiments run on CAM6 and one fully coupled experiment run on CESM version 1.3. The two atmosphere-only simulations are similar in that they are both forced with sea-ice, but the first experiment is forced with transient SIC, and the second set of experiments are forced with two different states of the SIC seasonal cycle.

In the transient SIC simulations, the model is forced with a time series of observational SIC from HadISST (Rayner et al. 2003). As mentioned above, these simulations were run on CAM6. Simulations were run with a fixed year 2000 radiative forcing, and global SSTs that follow a repeating seasonal cycle based on the 1979–2008 climatology from HadISST. In regions where SIC deviates from its monthly climatology by more than 10%, observed SSTs are used to make sure that SST increases due to sea ice melt would be captured. These simulations have two 8-member ensembles, but the only difference between the two ensembles is whether or not Arctic sea-ice thickness is transient or set to a fixed value. Sea ice thickness is held fixed at 1 meter across Antarctic sea ice in both ensembles. We combine the two 8-member ensembles into one 16-member ensemble, since we are only concerned with Antarctic sea ice.

The second set of atmosphere-only simulations we use was run on CAM6 according to the Polar Amplification Model Intercomparison Project protocol (PAMIP; Smith et al. 2019). These simulations were run for 14 months, with the first 2 months discarded for model spin-up, for 100 ensemble members. We use two experiments from this protocol, with two different states of sea ice as the forcing. The first experiment was the preindustrial SIC experiment, where simulations were forced with a seasonal cycle of SIC from when the global mean temperature represented the preindustrial time (13.67°C). The second experiment was the future Antarctic SIC experiment, where simulations were forced with a seasonal cycle of Antarctic SIC predicted to exist after 2°C of warming, when the global mean temperature is 15.67°C. SSTs for both of these experiments were fixed at a climatological seasonal cycle representing present-day conditions. Thus, the differ-

ence between these two simulations isolates the impact of Antarctic sea-ice changes between the preindustrial and future periods.

We also use monthly-mean output from a high-resolution version of CESM1.3 as part of the International Laboratory for High-Resolution Earth System Prediction (iHESP) project (Chang et al. 2020): CESM-HR. We analyze output from the coupled historical high-resolution simulations covering the period 1920–2005, which has 10 ensemble members. These high-resolution simulations have an atmospheric resolution of 0.25° and an ocean resolution of 0.1° . They have been shown to improve accuracy in the representation of global mean temperatures as well as the seasonal cycle of SSTs and mixed layer depths, compared to lower-resolution simulations. In the Southern Ocean, CESM-HR has simulated a weaker SST seasonal cycle compared to the low-resolution version, which is in better agreement with observations (Chang et al. 2020). Similarly, the Southern Ocean has some of the deepest mixed-layer depths during the summer, and the high-resolution model can capture these depths more accurately than the low-resolution version of the model (Chang et al. 2020). One area where CESM-HR struggles, is that it underestimates sea-ice concentration, in particular along the southern Weddell gyre. This has been attributed to an overactive polynya in the Weddell gyre (Chang et al. 2020). The SIC seasonal cycle in the low-resolution version generally has better agreement with observations than CESM-HR. However, this has been speculated to be a result of colder surface temperatures, colder than both CESM-HR and observations. Sea ice representation in the low-resolution model might be closer to observations than the CESM-HR, but it might be for the wrong reasons. These general biases present in CESM-HR should not make a large difference in the results presented in this dissertation, but they are still important to keep in mind.

CESM is a widely used Earth System Model that represents the Earth system well, but there is generally a large spread amongst CMIP6 models in their representation of Antarctic sea ice, especially its trends across the historical period (Roach et al. 2020). Figure 2.1 provides some context for what the representation of Antarctic sea ice looks like in the models we use, compared to ob-

servations. Figure 2.1 shows the seasonal cycle of Antarctic sea-ice area (SIA) from observations (from the NSIDC), CESM2 historical simulation, and CESM-HR historical simulation.

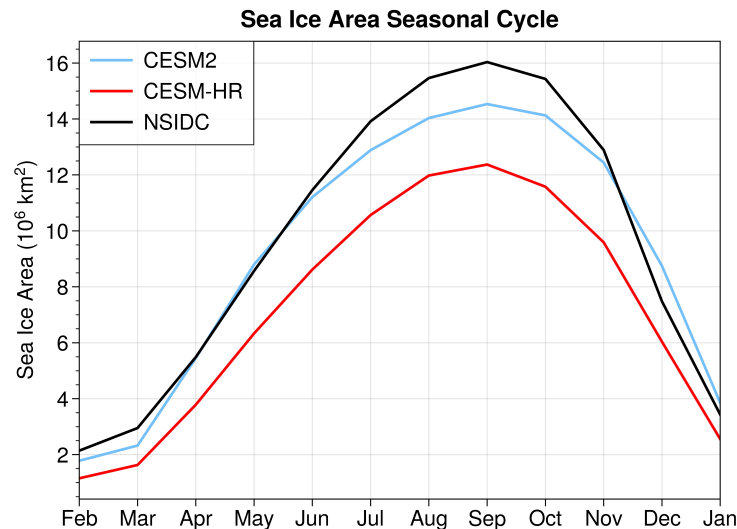


Figure 2.1: The monthly seasonal cycle of Antarctic sea-ice area from observations (black line), CESM2 historical simulation (blue line), and CESM-HR historical simulation (red line). The climatological seasonal cycle is taken across the common period of 1979–2005. The seasonal cycle shown for CESM2 and CESM-HR is the ensemble mean.

This figure shows that both CESM models underestimate sea-ice area during the seasonal sea-ice maximum and minimum. CESM2 is slightly closer to observations than CESM-HR, but as mentioned previously, that might not be indicative of an overall better representation of the Southern Ocean climate. Both CESM2 and CESM-HR have a relatively good representation of the seasonal cycle of Antarctic sea ice, especially compared to other CMIP6 models (Roach et al. 2020).

Figure 2.2 shows a time series of monthly Antarctic SIA from observations, CESM2, and CESM-HR. This figure highlights the model biases that exist, especially in the simulation of the observed Antarctic sea-ice trends. It is clear that both CESM2 and CESM-HR simulate too much Antarctic sea-ice loss over the historical period, but CESM-HR is closer to the observed timeseries. This is consistent with CMIP6 models, and is an ongoing area of research. These two figures

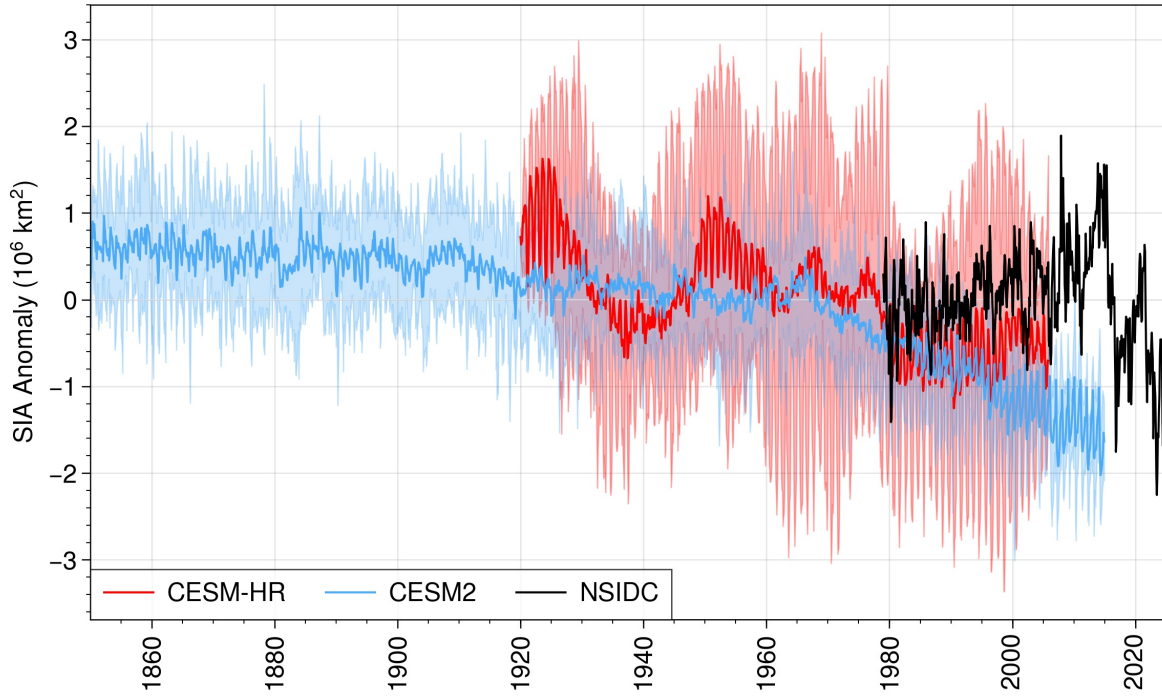


Figure 2.2: A time series of monthly Antarctic sea-ice area from 1850–2024. Observational data (black line), from the NSIDC, covers the period from 1979–2024, the CESM2 historical simulation (blue line) covers the period from 1850–2015, and the CESM-HR historical simulation (red line) covers the period from 1920–2005. The thick blue and red lines are the ensemble means, and the shading is the ensemble spread.

provide a representation of the potential sea-ice biases in these two models, which are important to keep in mind but do not preclude the use of these models in this work.

2.3 Analysis Methods

Unless otherwise noted, the long-term linear trend and mean seasonal cycle are removed from all data prior to the analyses. Regression coefficients are calculated as

$$\beta = \frac{\overline{x'y'}}{\overline{x'^2}} \quad (2.1)$$

where overbars denote the time mean and primes denote departures from the long-term time mean. For all regressions, x , the independent variable, is standardized. Correlation coefficients are calculated as

$$r = \frac{\overline{x'y'}}{\sigma_x \sigma_y} \quad (2.2)$$

where

$$\sigma_x = (\overline{x'^2})^{1/2}. \quad (2.3)$$

The statistical significance of regression analysis is computed by calculating the significance of correlation coefficients, r , using a Student's t -statistic and assuming the effective sample size N_{eff} is

$$N_{eff} = N \frac{1 - r_1 r_2}{1 + r_1 r_2}, \quad (2.4)$$

where N is the number of time steps, r_1 is the lag-1 autocorrelation of the first time series, and r_2 is the lag-1 autocorrelation of the second time series (Bretherton et al. 1999). This method of estimating effective sample size is critical for accurately taking into account autocorrelation within geospatial data.

Chapter 3

Interpretation of Recent Antarctic Sea-Ice Loss: The Key Role of the Southern Annular Mode During the Seasonal Sea-Ice Maximum¹

3.1 Introduction

Southern Hemisphere-mean sea-ice area (SIA) exhibited small increases from the early 1980s through 2015, but has decreased abruptly since, setting record negative anomalies in November 2016 and July 2023 (Figure 3.1; Parkinson 2019; Raphael and Handcock 2022; Turner et al. 2022; Liu et al. 2023; Roach and Meier 2024). In total, annual-mean Antarctic sea-ice extent decreased by roughly 2.5 million square kilometers between 2015 and 2023.

Various physical factors have been linked to both the weak increases in Antarctic sea ice between 1980–2015 and the dramatic losses thereafter (e.g., see discussion in Blanchard-Wrigglesworth et al. 2022). The early sea-ice increases have been linked to tropical phenomena such as the El Niño-Southern Oscillation (Ciasto et al. 2015; Hobbs et al. 2015; Meehl et al. 2016; Li et al. 2021; Chung et al. 2022; Bonan et al. 2024); freshening of the Southern Ocean via ice shelf melt and changes in precipitation/evaporation (Fyfe et al. 2012; Pauling et al. 2016; Purich et al. 2018; Sadai et al. 2020; Rye et al. 2020; Dong et al. 2022); Southern Ocean cooling (Blanchard-Wrigglesworth et al. 2021; Zhang et al. 2021); sea-ice drift (Sun and Eisenman 2021); changes in the surface flow linked to ozone depletion (Turner et al. 2009; Doddridge and Marshall 2017); and variations in the atmospheric flow over the Southern Ocean (Hall and Visbeck 2002; Stammerjohn et al. 2008; Simpkins et al. 2012; Raphael and Hobbs 2014; Kostov et al. 2017; Schemm 2018;

¹The results outlined in Chapter 3 have been published in *Communications Earth and Environment*: Boehm, C. L., Thompson, D. W. J., & Blanchard-Wrigglesworth, E. (2025). The key role of the Southern Annular Mode during the sea-ice maximum for Antarctic sea ice and its recent loss. *Communications Earth & Environment*, 6(1), 833. <https://doi.org/10.1038/s43247-025-02792-2>

Blanchard-Wrigglesworth et al. 2021; Roach et al. 2023). The recent declines have likewise been linked to a wide range of atmospheric and oceanic processes. These include wavelike variability in the atmospheric flow (Schlosser et al. 2018; Purich and England 2019), the Indian Ocean Dipole (Wang et al. 2019), changes in upper-ocean heat content (Meehl et al. 2019; Zhang et al. 2022; Purich and Doddridge 2023; Jena et al. 2024; Espinosa et al. 2024), and — as is the focus here — changes in the Southern Annular Mode (Turner et al. 2017; Stuecker et al. 2017; Schlosser et al. 2018; Zhang et al. 2022; Yadav et al. 2022; Turner et al. 2022).

The Southern Annular Mode (SAM) is characterized by variations in the strength of the westerly winds over the Southern Ocean (e.g., Thompson and Wallace 2000). In general, the contribution of the SAM to regionally varying changes in Antarctic sea ice is robust (Ciasto and Thompson 2008; Simpkins et al. 2012; Doddridge and Marshall 2017; Polvani et al. 2021), but its contribution to hemispheric-mean changes in sea ice is less clear, in large part because its signature in Antarctic sea ice varies in sign from one sector of the hemisphere to the next (e.g., Simpkins et al. 2012). For example, some studies have argued that the SAM contributed to the increases in Antarctic SIA from the 1980s-2000s (Turner et al. 2009; Sigmond and Fyfe 2010; Ferreira et al. 2015; Doddridge and Marshall 2017), whereas others have argued that the SAM had little influence on both the weak hemispheric-mean increases in sea ice through the 2000s (Bitz and Polvani 2012; Polvani et al. 2021; Dong et al. 2023) and the more pronounced decreases in Antarctic SIA since ~2015 (Polvani et al. 2021). To date, variations in the Southern Annular Mode (SAM) have not been conclusively linked to the large drops in Antarctic SIA centered around 2016/2017 and 2022/2023. As noted in Polvani et al. (2021): "the SAM/sea-ice extent relationship is tenuous".

Here we provide observational insights into the influence of the SAM on variations in hemispheric-mean Antarctic sea ice, especially over the past decade. We reveal that by far the largest influence of the SAM on annual-mean changes in SIA arises not from contemporaneous variations in the SAM, nor from variations in the SAM during the summer months when the effects of ozone depletion on the surface circulation are most clear. Rather, we demonstrate that the most pronounced influence of the SAM on annual-mean SIA arises from variations in the SAM during the sea-ice

maximum. The pronounced influence of the SAM on annual-mean SIA arises from a combination of the large contemporaneous relationships between the SAM and SIA during the sea-ice maximum, and the pronounced persistence of the sea-ice field during the ensuing months. We begin our analysis by exploring the lagged relationships between the SAM and SIA as a function of season.

3.2 Data and Methods

3.2.1 Observationally-Constrained Data

Monthly sea-ice concentration data are from NOAA/NSIDC Climate Data Record of Passive Microwave Sea Ice Concentration, Version 4 (Meier et al. 2021a) and the Near-Real-Time NOAA/NSIDC Climate Data Record of Passive Microwave Sea Ice Concentration, Version 2 (Meier et al. 2021b), and covers the period January 1979–July 2024. The sea-ice concentration is reported as the fraction of each grid cell that is covered by sea ice. Additional details about this dataset can be found in Chapter 2. The time series of SH-mean SIA was found by first multiplying the gridded sea-ice concentration data during each month by the area represented by each grid box, and then summing the resulting values over the SH. Similar results are derived using sea-ice extent, i.e., the area-integral of grid cells with sea-ice concentration greater than 15%.

Monthly mean values of the SAM index are from the NOAA CPC. Monthly mean values of the Niño3.4 index are also obtained from the NOAA CPC. Monthly 10-meter wind data is taken from ERA5 monthly averaged data on single levels dataset and has a horizontal resolution of $0.25^\circ \times 0.25^\circ$ (Hersbach et al. 2020). The SAM index and wind data covers the period from January 1979 to July 2024. Surface shortwave and longwave clear-sky radiative flux and cloud radiative effect (CRE) data are from the CERES-EBAF Edition 4.2 data product (Kato et al. 2018). This monthly data covers the period from March 2000–July 2024. Fluxes are positive when energy is deposited into the surface, and the CRE is defined as all-sky flux minus clear-sky flux. Observational SST data are from the HadISST dataset (Rayner et al. 2003). Despite that HadISST provides monthly data starting in 1871, we use the period from January 1979–July 2024 to align with the availability

of other datasets used. See Chapter 2 for more details on these datasets and the calculation of the SAM indices.

3.2.2 Model Output

Modeled monthly mean sea-ice concentration and geopotential height at 700 mb are from the CMIP6 historical and SSP5-8.5 simulations run on CESM2 (Danabasoglu et al. 2020). The SSP5-8.5 scenario is the fossil-fuel development scenario with an additional radiative forcing of 8.5 W/m² by 2100 and represents the scenario with very high greenhouse gas emissions (Riahi et al. 2017). The historical period simulations have 11 ensemble members, and the SSP5-8.5 simulations have three ensemble members. Additional details about the CESM2 simulations can be found in Chapter 2. Modeled monthly mean SAM indices are calculated using the 700 mb geopotential height anomalies, using the same procedure as used by the NOAA CPC for observed SAM indices, as described in Chapter 2. Analysis performed on this model output follows the same process as the observationally-constrained data, with the seasonal cycle removed and all output detrended before analysis.

3.2.3 Analysis Methods

Unless otherwise noted, the long-term linear trend and mean seasonal cycle are removed from all data prior to the analyses. The long-term linear trend is calculated across the entire 1979–2024 period for all variables except for the CERES radiative flux data. We emphasize that similar results are derived if the data are not detrended and if they are detrended with a base period of 1979–2015; the period of sea-ice increases (Figure A.1). As noted in the text, the broad structure of the results is also reproducible in data restricted to the 1979–2015 epoch (Figure 3.19). For the CERES radiative flux data, the base period is March 2000–2024 due to data availability. Additional details about the calculation of the regression/correlation coefficients, along with significance testing, can be found in Chapter 2.

3.3 Results

3.3.1 Seasonality of the influence of the SAM on SH SIA

The observational analyses are based on monthly gridded sea-ice concentration data, radiative flux data, wind data, and sea surface temperature data from satellite and reanalysis products (Methods). The time series of the SAM is defined as the leading principal component time series of monthly-mean 700 mb height anomalies south of 20°S (Methods). By definition, positive values of the index correspond to stronger than normal westerlies over the Southern Ocean, and vice versa. Analyses of sea ice and atmospheric data are based on the period January 1979 to July 2024; analyses of radiative flux data are based on the period March 2000–July 2024. Unless otherwise noted, the long-term mean seasonal cycles and trends are removed from the data before performing the analyses. Details of the analysis procedure and data sources are provided in the Methods section.

We focus on the seasonally varying and lagged signature of the SAM in SH SIA. The SAM is key for Antarctic climate for a range of reasons: 1) It is the most prominent pattern of internal atmospheric variability in the mid-high latitude SH atmospheric circulation and thus accounts for a large fraction of the variance in the surface flow around Antarctica (Thompson and Wallace 2000); 2) It accounts for the majority of the SH circulation response to both stratospheric ozone depletion (Thompson and Solomon 2002; Polvani et al. 2011) and increasing greenhouse gases (Kushner et al. 2001; Arblaster and Meehl 2006); and 3) It accounts for a notable component of the SH response to El Niño-Southern Oscillation (ENSO), especially in summer (L’Heureux and Thompson 2006).

To set the stage, Figure 3.1 shows the SH SIA and SAM indices as a function of month. As noted in the Introduction, SH mean SIA increased weakly through the mid-2010s and then dropped markedly after 2015, with record negative anomalies reported in 2016 and 2023 (Figure 3.1a; Parkinson 2019; Raphael and Handcock 2022; Liu et al. 2023). The SAM index exhibits considerable variability from one month to the next but has also exhibited a weak positive trend throughout the period of record (Figure 3.1b). The positive trend is most clear during the summer months and

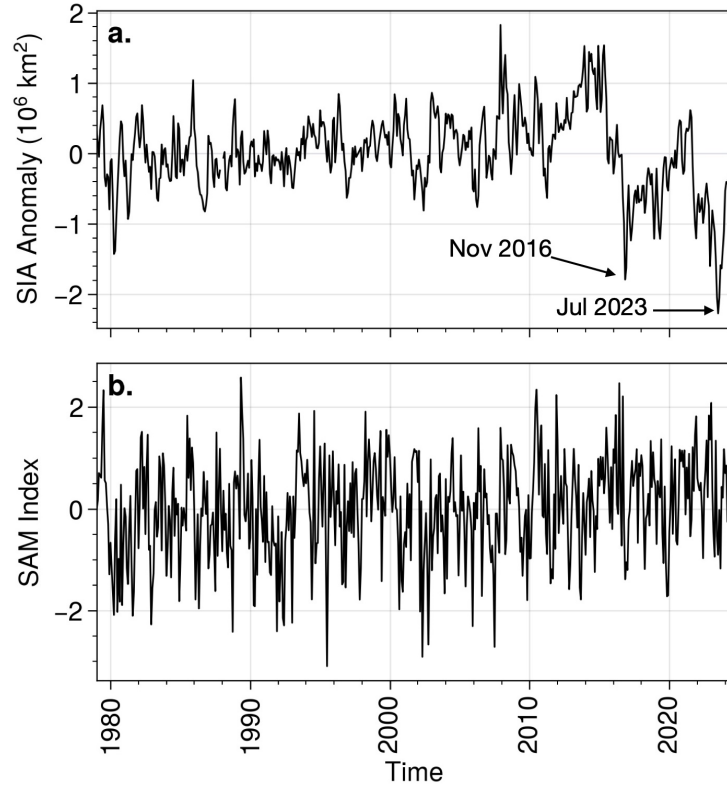


Figure 3.1: Observed monthly-mean values of (a) Antarctic sea-ice area anomalies (SIA) and (b) the Southern Annular Mode (SAM). The time series are deseasonalized but not detrended. Months with record negative SIA anomalies are denoted on (a).

over the period of largest ozone losses through ~ 2000 (Marshall 2003; Thompson et al. 2011; Polvani et al. 2011; Fogt and Marshall 2020).

From Figure 3.1a it is visually apparent that SH SIA exhibits notable persistence for up to a few months (see also Holland et al. 2013; Ordoñez et al. 2018; Marchi et al. 2019; Libera et al. 2022), particularly over the past decade (Hobbs et al. 2024). Figure 3.2a probes this persistence as a function of season. The first row shows the auto-regression of SIA during January, i.e., it shows SIA in units km^2 at the lags indicated on the x-axis regressed onto standardized values of SIA during January. Subsequent rows show analogous lag results based on standardized values of SIA for the months indicated on the y-axis. For example, results at lag zero in the October row indicate the regression of October values of SIA onto standardized October values of SIA; results at lag seven in the October row indicate the regression of May values of SIA (during the following calendar

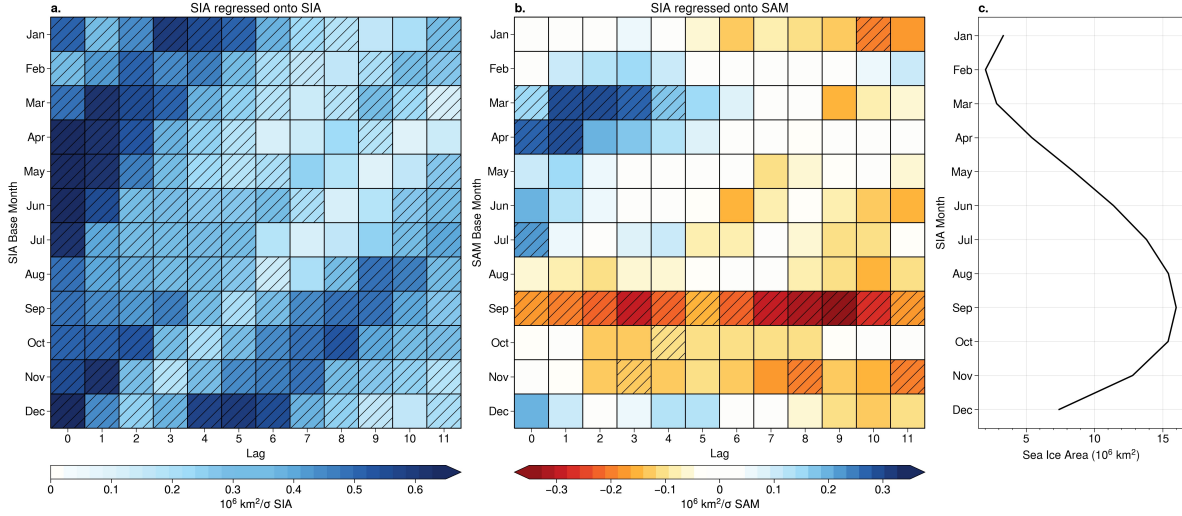


Figure 3.2: The regression for monthly-mean values of Southern Hemisphere-mean sea-ice area (SIA) regressed onto the standardized values of (a) SIA and (b) the Southern Annular Mode (SAM) index. The months on the y-axis indicate the month used as a basis for the regression; the values on the x-axis indicate the lag with respect to the basis month. For example, the first row in (b) shows SIA in units km^2 at lags indicated on the x-axis regressed onto standardized values of the SAM index during January. All data used in panels (a) and (b) are detrended with respect to the long-term mean climatology. Panel (c) shows the climatological seasonal cycle of Antarctic SIA. Hatching indicates regressions that are statistically significant at the 95% confidence intervals. See text for details.

year) onto standardized October values of SIA; etc. Note that the lag zero results are equivalent to the year-to-year standard deviation of SH mean SIA time series for the months indicated on the y-axis. The results in Figure 3.2c show the climatological-mean seasonal cycle of SIA as a point of reference for interpreting the seasonal cycle in the persistence. Corresponding correlations for Figure 3.2a,b are shown in Figure 3.3, and hatching indicates regions where the correlations exceed the 95% level (Methods). Correlations that are significant at the 95% level in Figure 3.3 are at least $\sim \pm 0.4$, with correlations reaching upwards of $\sim \pm 0.6$.

The results highlight the considerable persistence of SIA from one month to the next, with sea-ice anomalies persisting for several months during all times of the year (Holland et al. 2013; Ordoñez et al. 2018; Marchi et al. 2019; Libera et al. 2022). They also highlight a unique pattern of reemergence in sea-ice anomalies that is most clear after the sea-ice maximum in September and October. Sea-ice anomalies during the sea-ice maximum persist for several months, reach a minimum in the following summer season (i.e., around lags 4–5, which correspond to January–

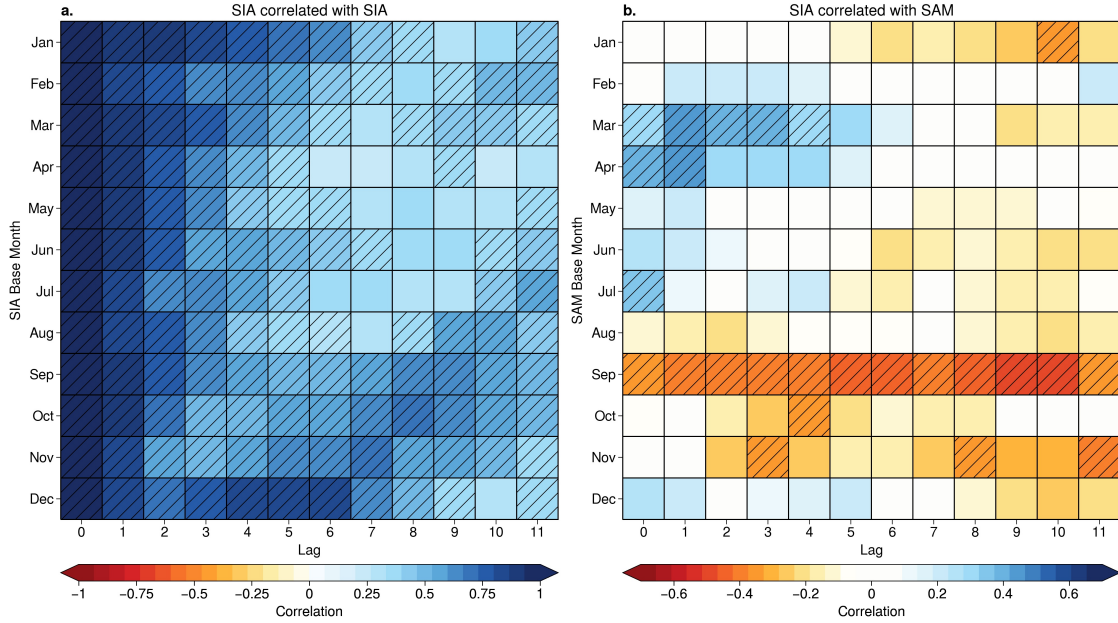


Figure 3.3: As in Figure 3.2 but for correlations of SIA with itself and the SAM. Note that positive correlations are shade blue to be consistent with the regressions in Figure 3.2

February), and then remerge during the following season of sea-ice growth (i.e., around lags 7–8, which correspond to the following April–May). The sea-ice anomaly reemergence mechanism was first described for Arctic sea ice (Blanchard-Wrigglesworth et al. 2011); Figure 3.2a indicates it also emerges in the Antarctic, which is consistent with previous work (e.g., Holland et al. 2013). The reemergence of SIA anomalies from spring to the following autumn has been linked to oceanic processes (Holland et al. 2013, 2017, 2018; Ordoñez et al. 2018; Marchi et al. 2019; Libera et al. 2022; Purich and Doddridge 2023) and is reminiscent of that found in association with extratropical SSTs (e.g., Alexander et al. 1999). The reemergence is most clear following the sea-ice maximum and gives rise to significant persistence in the SIA field through the following winter (i.e., hatching indicates significance at the 95% confidence level; see also Purich and Doddridge 2023 Fig. 4).

Figure 3.2 explores the corresponding seasonally-varying covariability between SIA and the SAM index. In this case, the first row shows SIA in units km^2 at the lags indicated on the x-axis regressed onto standardized values of the SAM during January; subsequent rows show analogous results for standardized values of the SAM during the months indicated on the y-axis. For example, results at lag seven in the October row indicate the regression of May values of SIA (during the

following calendar year) onto standardized October values of the SAM, etc. Blue shading indicates increases in sea ice, and vice versa. The results in Figure 3.2b highlight two key aspects of the relationships between the SAM and hemispheric mean SIA that have not been widely appreciated in previous work:

1. The sign of the linkages between SIA and the SAM change from one season to the next. The regressions between the SAM and SIA are positive (that is, the positive polarity of the SAM gives rise to increases in SIA) during the annual sea-ice minimum between February and April, but negative during the annual sea-ice maximum between August and November. The in-phase relationship between the SAM and SIA during the annual sea-ice minimum is consistent with the sign of the relationships reported in Doddridge and Marshall (2017) and Polvani et al. (2021). The out-of-phase relationship between SIA and the SAM during the annual sea-ice maximum is not expected based on previous work. Simpkins et al. (2012) highlight regional decreases in sea ice associated with the SAM during September, October, and November, but they do not probe the corresponding changes in hemispheric mean SIA or the results as a function of lag. Holland et al. (2018) demonstrate seasonally-varying lagged relationships between sea ice and the Amundsen Sea Low, but do not consider the hemispheric-mean impacts of the SAM.
2. Consistent with the persistence in the sea-ice field, the SAM-induced changes in sea ice persist for months after the largest anomalies in the circulation. In the case of the sea-ice maximum centered around September, the positive polarity of the SAM leads to decreases in SIA that last through the following fall and winter seasons, up to 11 months in the future. The regression coefficients are statistically significant for lags up to 3–4 months following the sea-ice minimum centered around March, and for lags up to 11 months following the sea-ice maximum during September. Notably, the relationship between the SAM and lagged SIA is insignificant during most other times of the year.

The top row in Figure 3.4 shows the spatially varying signatures of the sea-ice anomalies that underlie the hemispheric mean results in the September row of Figure 3.2b. Figure 3.4a-d show

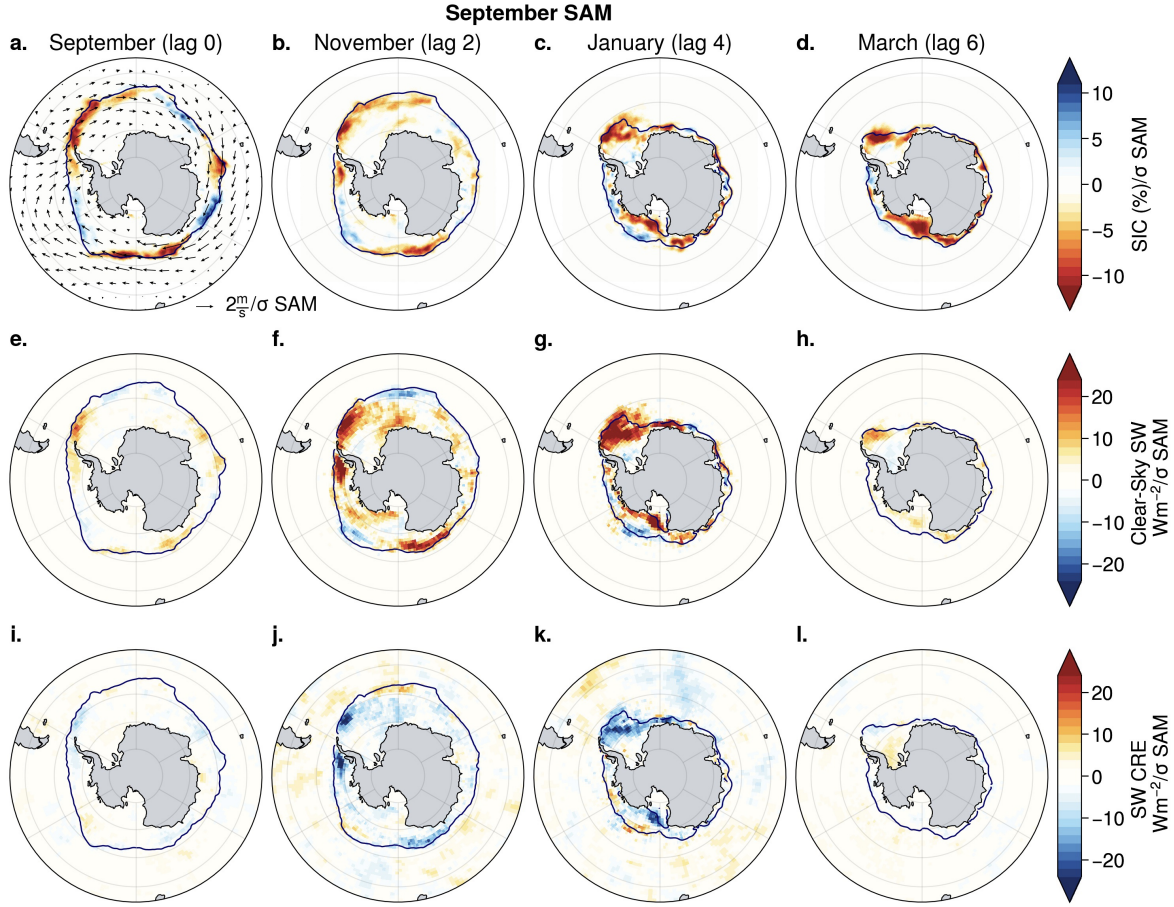


Figure 3.4: Regressions onto standardized September values of the Southern Annular Mode index. (a-d) Sea-ice concentration (SIC) for the indicated months regressed onto standardized September values of the Southern Annular Mode (SAM) index. Vectors in (a) show results for September 10-meter winds. (e-h) As in (a-d) but for clear-sky surface shortwave (SW) fluxes regressed onto standardized September values of the SAM index. (i-l) As in (a-d) but for cloudy surface SW fluxes (SW cloud radiative effects (CRE)) regressed onto standardized September values of the SAM index. Black contours indicate where the climatological-mean monthly mean sea-ice concentration is at least 15%. Data are detrended with respect to the long-term mean climatology. Flux anomalies are positive downward and are based on the period 2000–2024.

September, November, January, and March sea-ice anomalies regressed on September values of the SAM index; the vectors in Figure 3.4a show the September near-surface wind anomalies regressed onto September values of the SAM index for context. Blue shading again indicates increases in sea ice, and vice versa. The area averages of the results in Figure 3.4a-d are equal to the results in the September row of Figure 3.2b. The climatological ice edge is indicated by the solid black contour.

Circulation anomalies associated with the positive polarity of the SAM are dominated by a zonally-symmetric strengthening of the circumpolar westerlies around Antarctica juxtaposed with

poleward wind anomalies upstream of the Antarctic peninsula (vectors in Figure 3.4a). The largest contemporaneous sea-ice anomalies arise along the equatorward edge of the sea-ice cover (shading in Figure 3.4a) and are largely consistent with the signature of the SAM in the wind field, i.e., the most prominent regions of low sea ice (red shading) arise along $\sim 60^\circ\text{S}$ and in regions to the north of the Ross, Weddell and Davis Seas where the near-surface flow is anomalously southward. When summed over the hemisphere, the regions of sea-ice losses exceed those of sea-ice increases and thus September variations in the SAM are associated with a net decrease in SIA during September (Figure 3.2b). At increasingly longer lags, the decreases in sea ice found during September follow the seasonal cycle of the sea-ice edge, with sea-ice decreases retreating to the periphery of Antarctica during the summer (Figure 3.4b-d).

Figure 3.5 shows companion results for variations in the SAM during the annual sea-ice minimum centered around March. In this case, the SAM-related wind anomalies have a northward component over the Ross, Davis, and Weddell Seas that is consistent with cold temperature advection in these regions. The most prominent northward anomalies overlie regions of positive sea-ice anomalies that give rise to the increases in SIA in the March row of Figure 3.2b. The sea-ice anomalies initiated during the sea-ice minimum persist along the sea-ice edge as it expands during winter, albeit as also indicated in Figure 3.2b their amplitude weakens through the following spring.

What drives the persistence of the sea-ice anomalies associated with the SAM? A variety of factors give rise to memory in SH sea ice, including upper ocean heat content and radiative feedbacks (e.g., Holland et al. 2013; Marchi et al. 2019; Libera et al. 2022; Purich and Doddridge 2023). The results in the bottom two rows of Figure 3.4 suggest clear-sky shortwave (SW) feedbacks play a key role in maintaining the SAM-induced anomalies in the sea-ice field. The middle row in Figure 3.4 shows clear-sky SW fluxes from CERES regressed onto September values of the SAM index; the bottom row shows the same results but for CERES SW cloud radiative effects (CRE). Red values indicate anomalous fluxes into the surface. The regions of persistent sea-ice decreases (top row) are overlaid by regions of clear-sky SW flux anomalies into the surface (middle

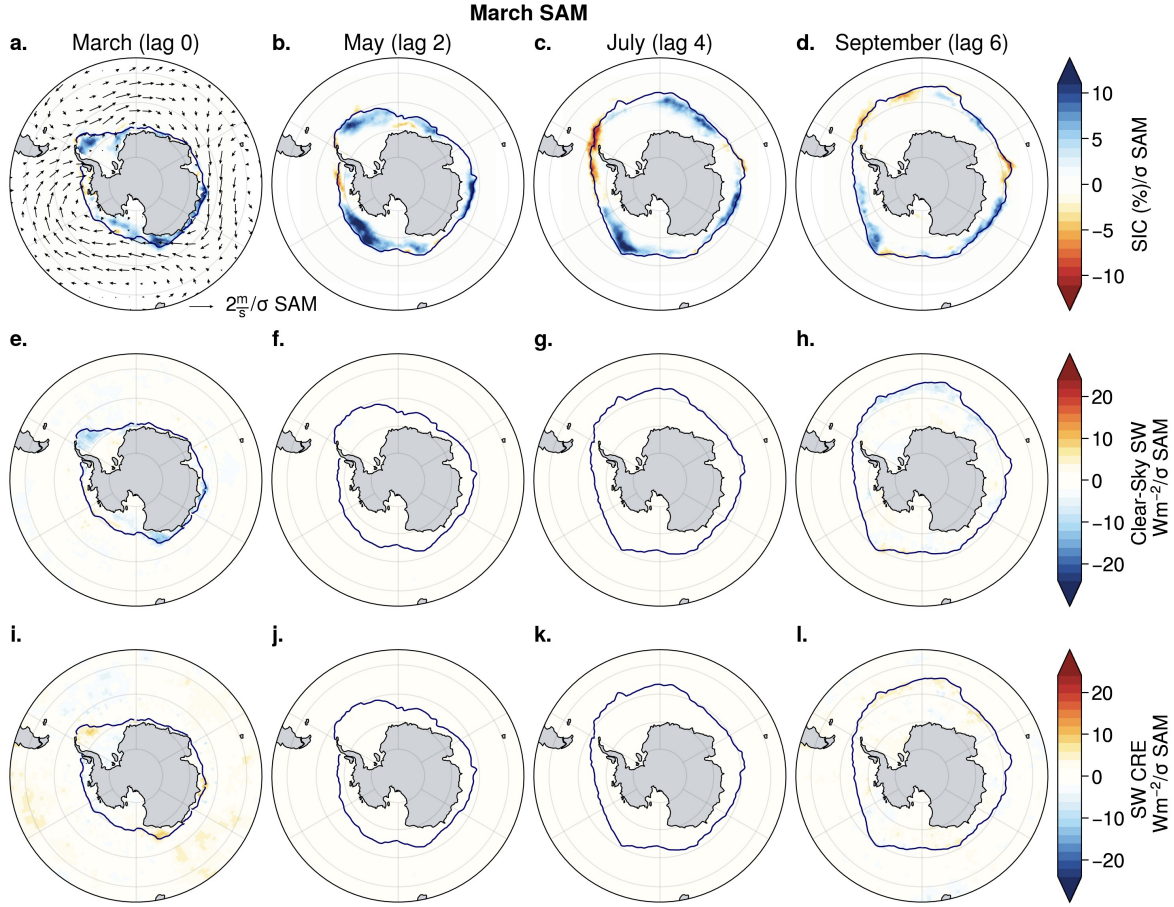


Figure 3.5: As in Figure 3.4, but for regressions onto standardized March values of the SAM index.

row). The anomalous clear-sky SW fluxes are consistent with changes in surface albedo associated with the sea-ice anomalies and act to support the anomalous changes in surface temperature associated with the SAM-driven changes in sea ice. The SW CRE act in the opposite sense: Regions of sea-ice loss (top row) are overlaid by regions of anomalous upward SW CRE (bottom row). While the SW CRE anomalies counteract the clear-sky SW anomalies, the latter are substantially larger, thus dominating the SW response to the SAM-driven changes in sea ice.

The factors that give rise to the long persistence of winter SAM-induced anomalies in SH SIA are further probed in Figure 3.6. The solid black line shows the regression of SH-mean SIA regressed onto September values of the SAM as a function of lag, i.e., the results are identical to the September results from Figure 3.2b. Note that the amplitudes for the SH-mean SIA in Figure 3.6 are given as 10^7 km^2 to align with the range of the y-axis. The solid blue and grey

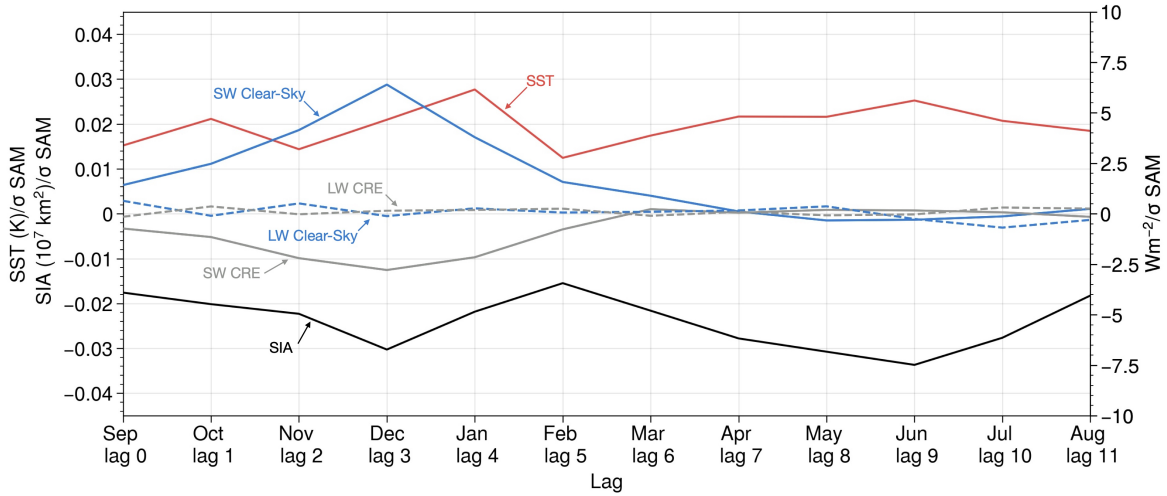


Figure 3.6: Regressions onto standardized September values of the SAM index as a function of lag. Black line: The regression of Southern Hemisphere-mean sea-ice area (SIA) as a function of lag onto standardized September values of the Southern Annular Mode (SAM) index. Grey and blue solid lines: As in the black line, but for shortwave (SW) cloud radiative effects (CRE) and SW clear-sky fluxes, respectively. Grey and blue dashed lines: As in the black line, but for longwave (LW) CRE and clear-sky fluxes, respectively. Red line: As in the black line, but for sea surface temperatures (SST). Amplitudes for all fluxes are given on the right axis; amplitudes for SST anomalies and SIA anomalies are indicated on the left axis. The fluxes and SST anomalies are averaged over regions where the sea-ice concentration anomalies for the corresponding month are negative. All data are detrended with respect to the long-term mean climatology. Fluxes are given over the period 2000–2024. See text for details.

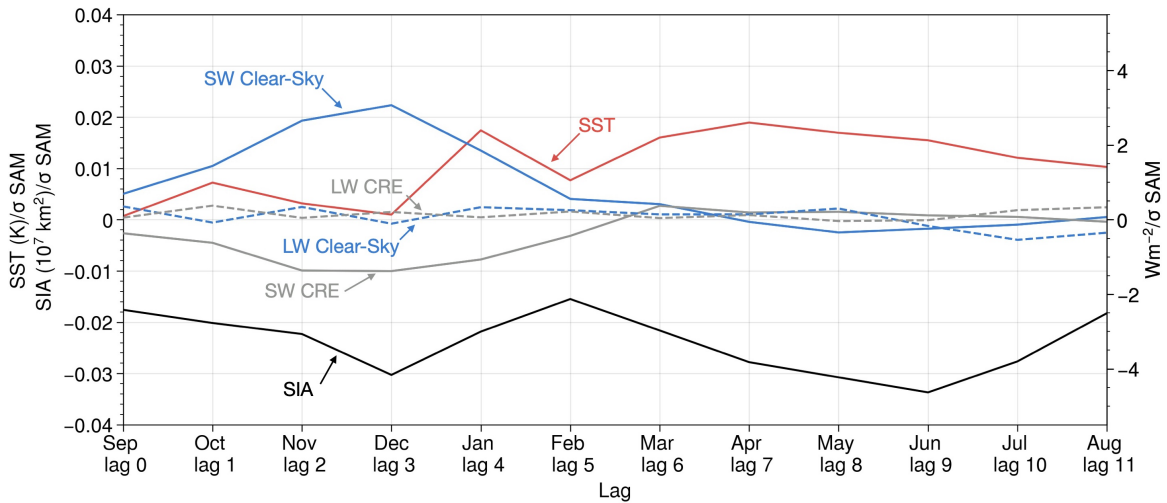


Figure 3.7: As in Figure 3.6 but fluxes and SST anomalies are averaged over all regions with sea-ice concentration anomalies, not only where anomalies are negative.

lines show companion results for the SW clear-sky and SW CRE, respectively, where the fluxes are averaged over regions where the sea-ice concentration anomalies for the corresponding month

are negative. For example, the values indicated by the blue line for November correspond to the clear-sky SW fluxes from Figure 3.4f averaged over regions where the sea-ice concentration anomalies are negative in Figure 3.4b. We focus on regions where the concentrations are negative so that the results indicate radiative flux anomalies over regions of sea-ice loss. Nevertheless, similar results are derived when the fluxes are averaged over regions of both positive and negative sea-ice anomalies (Figure 3.7). As evidenced in Figure 3.6, the clear-sky SW fluxes act to warm the surface and thus support the persistence in sea-ice loss, whereas the SW CRE act to cool the surface. The corresponding changes in the longwave (LW) fluxes (dashed blue and grey lines) are weak during all lags. Note that the small changes in LW CRE suggest that the changes in SW CRE are driven by variations in low-level clouds that have a weak signature in the LW since they are close to the surface temperature. The implied changes in low-level clouds over regions of sea-ice loss are reminiscent of similar relationships between regions of open water and low-level clouds over the Arctic (Kay and Gettelman 2009). The SW flux anomalies in Figure 3.6 decrease rapidly after roughly month six with the onset of the following winter. The persistence of the sea-ice anomalies beyond March can be understood from the thermal inertia of the ocean mixed layer. The solid red line in Figure 3.6 is constructed in the same manner as the flux results, but for anomalies in sea-surface temperature (SST) from the HadISST data set. Ocean heat content from the Argo data product does not consistently sample regions poleward of 65°S (Roemmich and Gilson 2009); thus, we use SSTs over regions of sea-ice anomalies as a proxy for heat storage in the ocean mixed layer (see Ciasto and Thompson 2007; Holland et al. 2017). Periods of low sea ice during September are followed by positive SST anomalies that peak in summer and persist through the following fall and winter months. The persistence of the SST anomalies is not due to shared low-frequency variability in the SAM and SST data: Both datasets are detrended before the analyses, and we confirmed that the regression coefficients drop to zero at negative lags. As noted earlier, the persistence in ocean heat content is also thought to underlie the reemergence of SH sea-ice anomalies (Holland et al. 2013, 2017, 2018; Ordoñez et al. 2018; Marchi et al. 2019; Libera et al. 2022; Purich and Doddridge 2023).

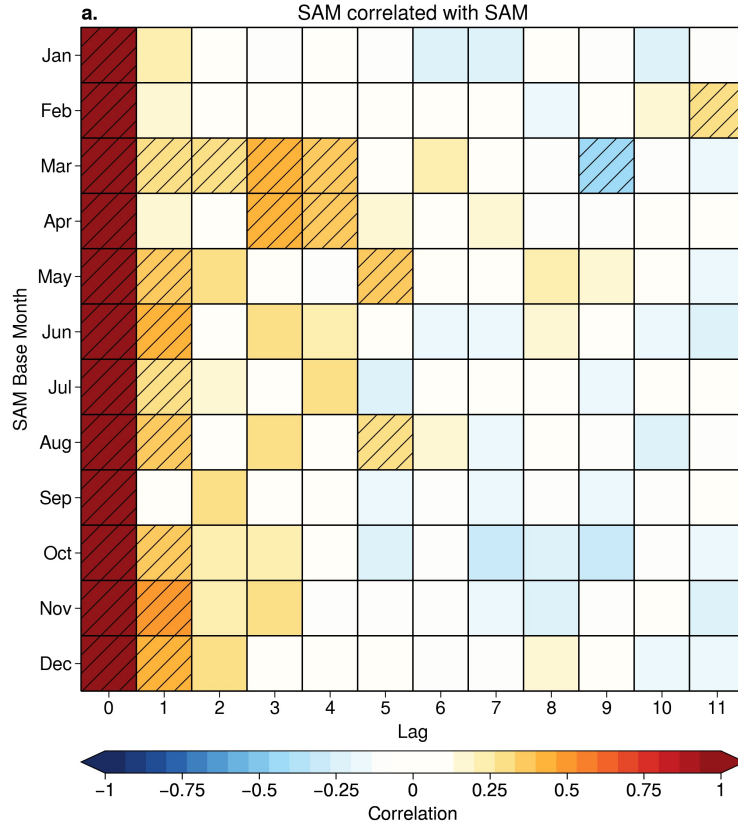


Figure 3.8: As in Figure 3.2a, but for correlations of the SAM with itself

Why is the amplitude and persistence of the signature of the SAM in SIA so much more pronounced after September than in the surrounding months? The persistence in SIA can not be traced to persistence in the SAM itself — there is little memory inherent in the SAM index from one month to the next, particularly following the sea-ice maximum (Figure 3.8). Presumably, the analysis is not sensitive to the exact days used in the analysis, and similar results would emerge from analyses based on, say, the last weeks of August through the first weeks of October. Nevertheless, it is notable that results based on July and August are marked by much weaker SW clear-sky fluxes at positive lag, which suggests those months are less prominent since the SW fluxes — and thus SW feedbacks — are relatively weak at that time of year. For example, Figure 3.9 and Figure 3.10 show results analogous to Figure 3.4 but for variations in the SAM during July and August. The sea-ice anomalies correlated with July variations in the SAM are dominated by positive anomalies north of the Amundsen Sea and to the east of the Weddell Sea, consistent with the

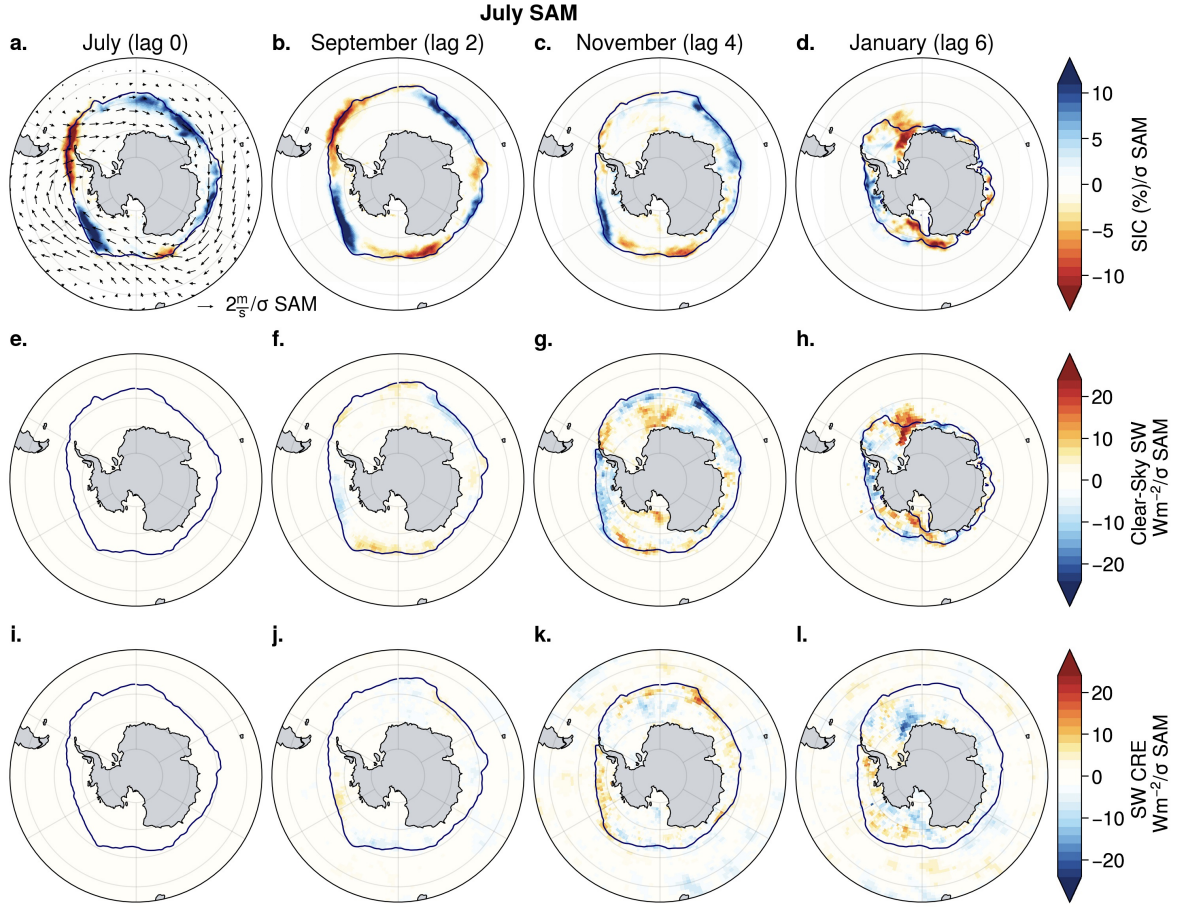


Figure 3.9: As in Figure 3.4, but for regressions onto standardized July values of the SAM index.

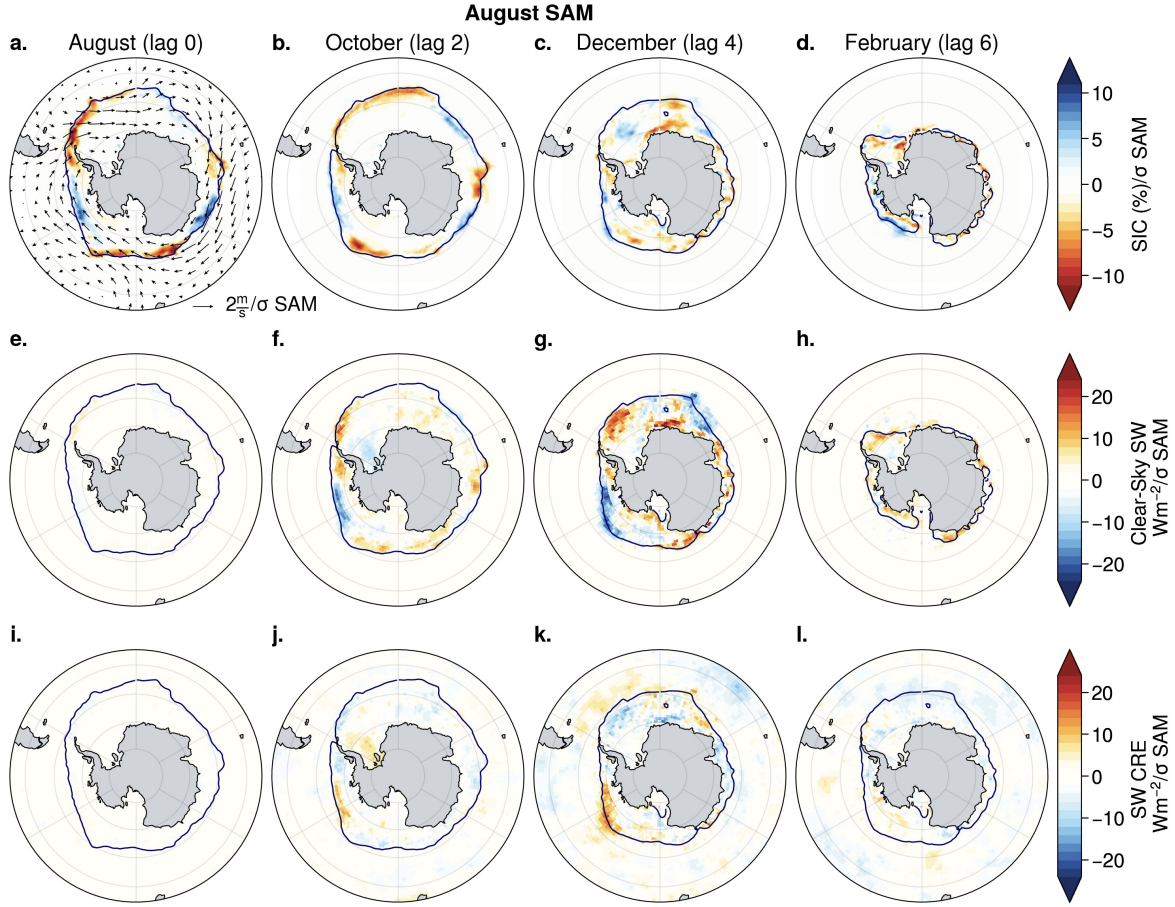


Figure 3.10: As in Figure 3.4, but for regressions onto standardized August values of the SAM index.

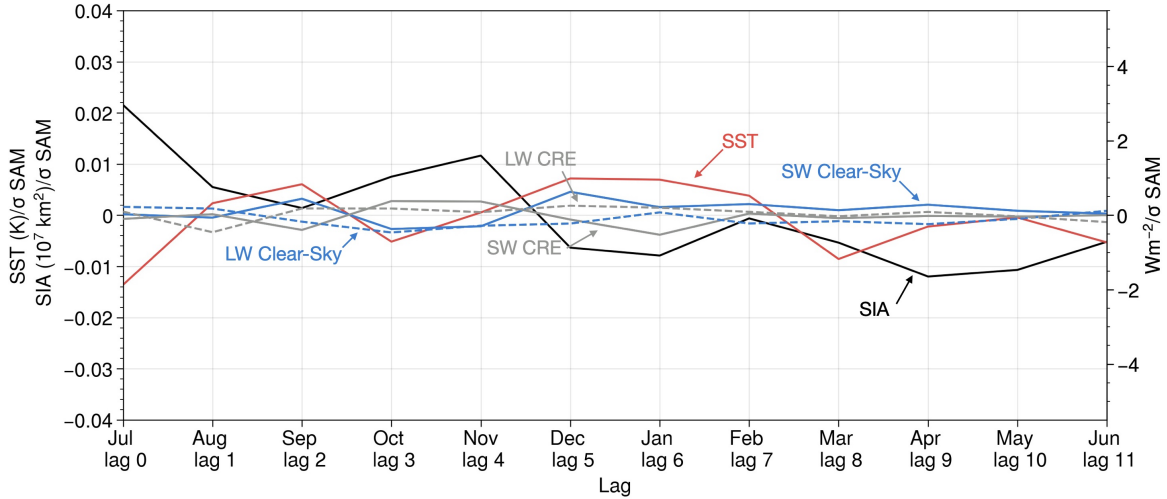


Figure 3.11: As in Figure 3.6, but for regressions onto standardized July values of the SAM index.

overlying northward component of the wind anomalies, whereas the sea-ice anomalies associated with August variations in the SAM are more varied, with areas of positive and negative anomalies of similar amplitude. In both cases, the sea-ice anomalies are marked by relatively weak clear-sky shortwave flux anomalies during the following months (compare Figure 3.9e,f and Figure 3.10e,f with Figure 3.4e,f). Additionally, Figure 3.11 and Figure 3.12 show results analogous to Figure 3.6 but for regressions onto the SAM during July and August. As with Figure 3.9 and Figure 3.10, it is clear that there are weak flux anomalies during the following months. These weak flux anomalies then also lead to weak SST anomalies later in the year. As noted earlier (Figure 3.2b), results based on months later in the spring (e.g., October and November) are marked by weak hemispheric mean sea-ice anomalies. The weak SIA anomalies arise since the regions of positive and negative sea-ice anomalies largely cancel at this time of year due to regional differences in the pattern of wind anomalies.

3.3.2 The key role of the SAM During the seasonal sea-ice maximum

The persistence of the circulation-induced sea-ice anomalies from one month to the next suggests that circulation anomalies during the sea-ice maximum and — to a lesser degree — the sea-ice minimum have a notable impact on annual mean changes in SIA. The top panel in Figure 3.13

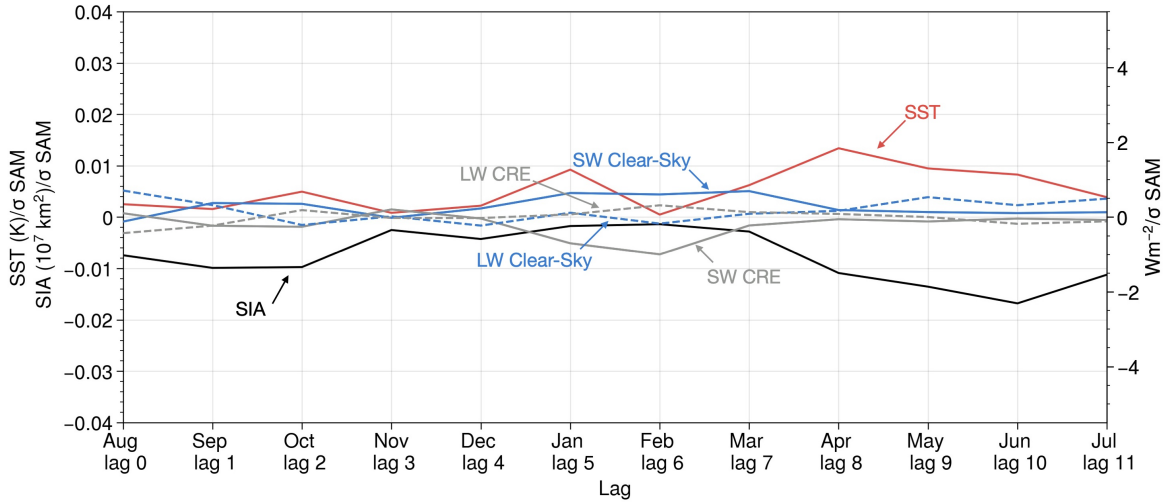


Figure 3.12: As in Figure 3.6, but for regressions onto standardized August values of the SAM index.

shows the regression of annual-mean SIA anomalies onto the SAM as a function of month, where the annual-mean SIA anomalies are formed by averaging SIA over the 12 consecutive months starting from the base month of the regression. For example, the September bar in Figure 3.13a is found by regressing SIA averaged over September-August (of the following year) onto September values of the SAM index.

As expected from Figure 3.2b, the positive polarity of the SAM leads to increases in annual-mean SIA following the sea-ice minimum but decreases following the sea-ice maximum. The influence of the SAM on year-round SIA is particularly notable following September anomalies in the atmospheric circulation. In terms of variance explained, circulation anomalies during the sea-ice maximum dominate the influence of the SAM on annual mean sea ice: Variations in the SAM during September explain over 30% of the annual-mean variance in SIA, whereas variations in the SAM during other months explain only a small fraction of the year-to-year variance (Figure 3.14).

The contribution of September variations in the SAM to year-round values of SIA is also visually apparent when the time series of SIA are discretized by year (Figure 3.13b). Here, each line shows monthly-mean SIA anomalies for all calendar years starting in September. The colors assigned to each line correspond to the September values of the SAM for that year. To simplify the figure, only years that had a September SAM value exceeding ± 1 standard deviation are shown

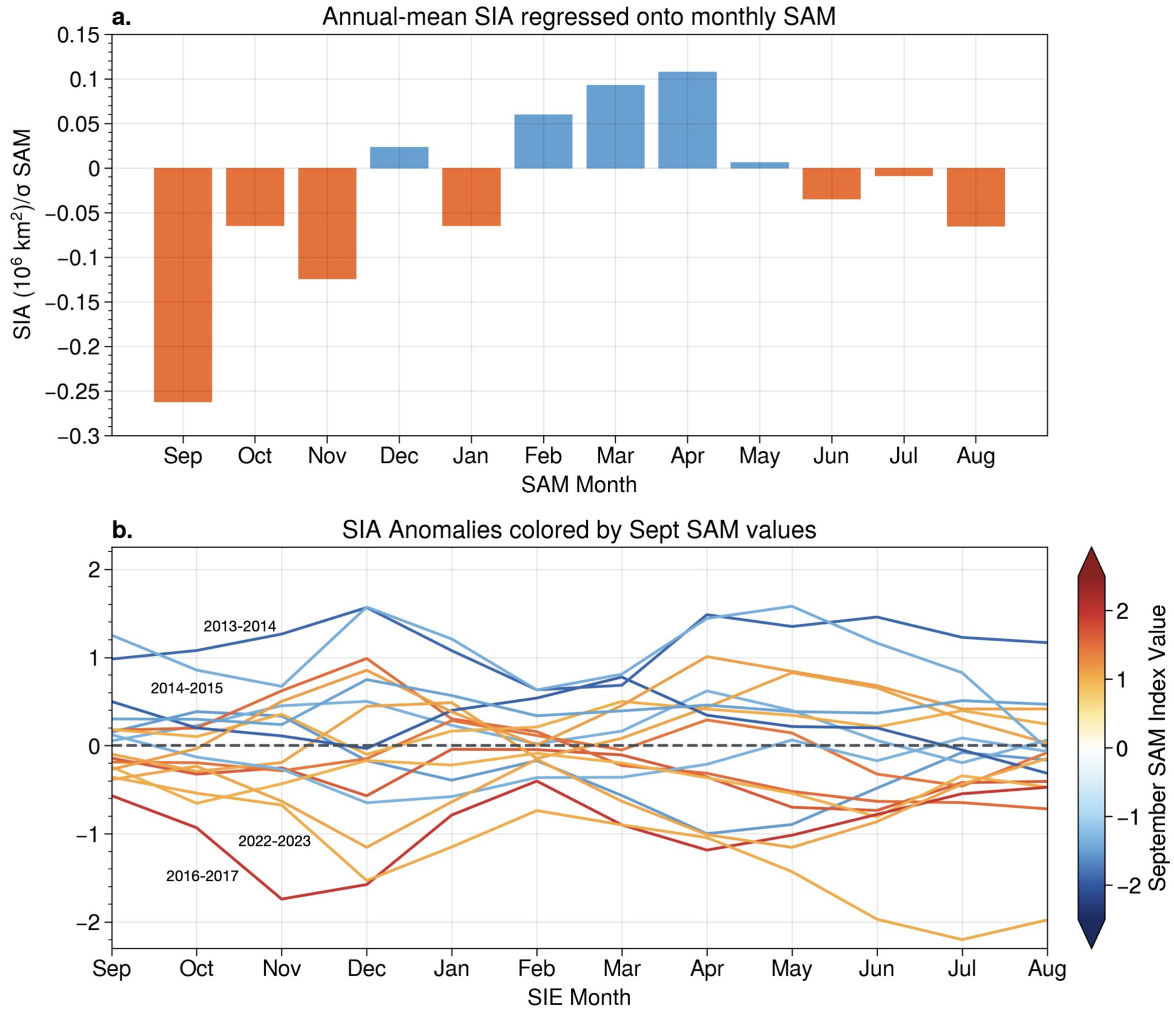


Figure 3.13: Quantifying the seasonal relationships between sea-ice area and the Southern Annular Mode. (a) The regression of annual-mean sea-ice area (SIA) anomalies onto monthly values of the Southern Annular Mode (SAM) index, where the annual means are formed from the 12-month period starting on the month indicated on the x-axis. For example: Results for September indicate September-August (during the following year) mean values of SIA regressed onto September values of the SAM index, etc. (b) Monthly-varying values of monthly SIA anomalies discretized by the value of the SAM index during September (colors). Years with anomalously high or low SIA are denoted on the plot. September SAM indices are standardized and only years with September SAM index values exceeding ± 1 standard deviation are shown. Figure concept inspired by Fig. 4 in Doddridge and Marshall (2017). All data are detrended with respect to the long-term mean climatology.

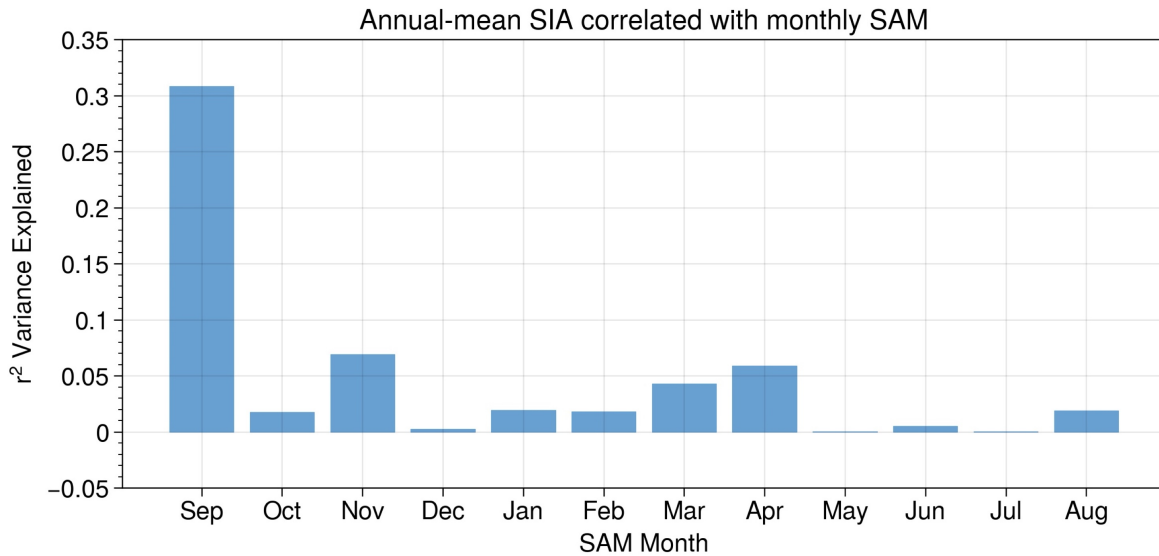


Figure 3.14: As in Figure 3.13a, but for the variance in annual-mean SIA anomalies explained by variations in the SAM index during the indicated month. For example: Results for September indicate the correlation squared between September-August (during the following year) mean values of SIA and September values of the SAM index, etc.

(results including all years are shown in Figure 3.15). There is a clear correspondence between years that had large positive SIA anomalies and years that had large negative September SAM indices, and vice versa. Years that had particularly large positive or negative SIA anomalies are labeled and exhibit marked correspondence to September values of the SAM. Importantly, years with large September SAM values had substantial SIA anomalies that not only persisted during the spring but throughout the year, consistent with results shown in Figure 3.2b and Figure 3.13a.

As noted in the Introduction, the SAM is significantly correlated with variations in ENSO. However, the most prominent linkages between the SAM and ENSO are limited to the summer months (L’Heureux and Thompson 2006), whereas the most prominent contribution of the SAM to hemispheric mean sea ice arises following the sea-ice maximum. Figure 3.16 shows Figure 3.13a reproduced using the Niño3.4 index obtained from the NOAA Climate Prediction Center (Methods). The contribution of ENSO to annual-mean changes in SIA is clearly much smaller than that associated with the SAM, not only following September, but following other months of the year as well (compare Figure 3.13a with Figure 3.16). A more detailed analysis of the signature of ENSO in hemispheric-mean SIA is beyond the scope of the current study.

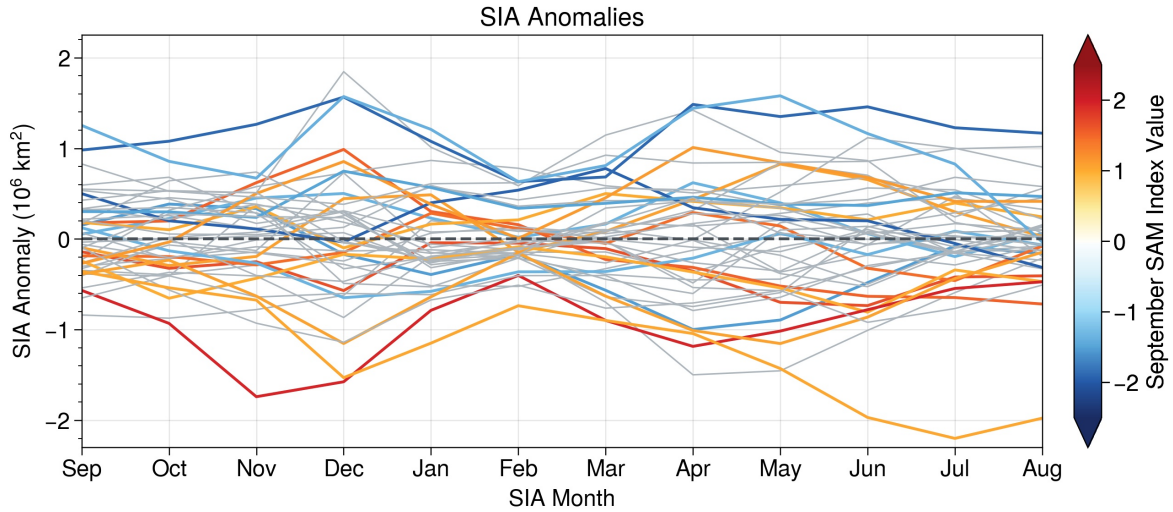


Figure 3.15: As in Figure 3.13b, but with all other years that were not shown in Figure 3.13b shown in light gray lines; i.e., all years where the standardized September SAM was within ± 1 standard deviation.

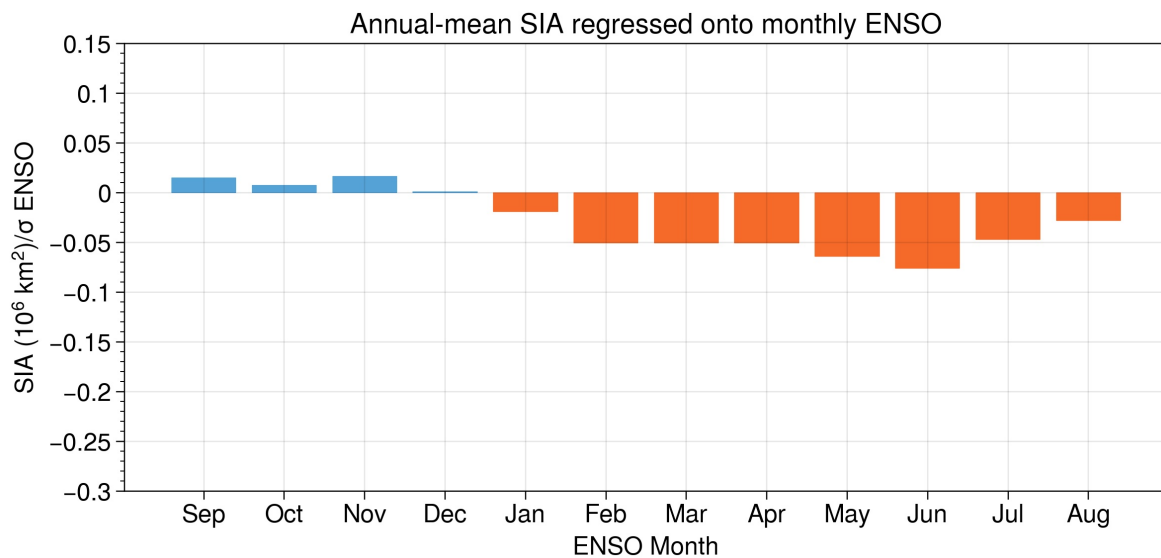


Figure 3.16: As in Figure 3.13a, but using the Niño3.4 index obtained from the NOAA Climate Prediction Center.

The linkages between variations in the SAM during the sea-ice maximum and annual mean changes in SH-mean SIA have implications for understanding the large losses in SIA over the past decade. Figure 3.17 shows September values of the SAM index (gray) superposed on SIA during alternating subsequent months (black). That is: The gray lines in all rows show September

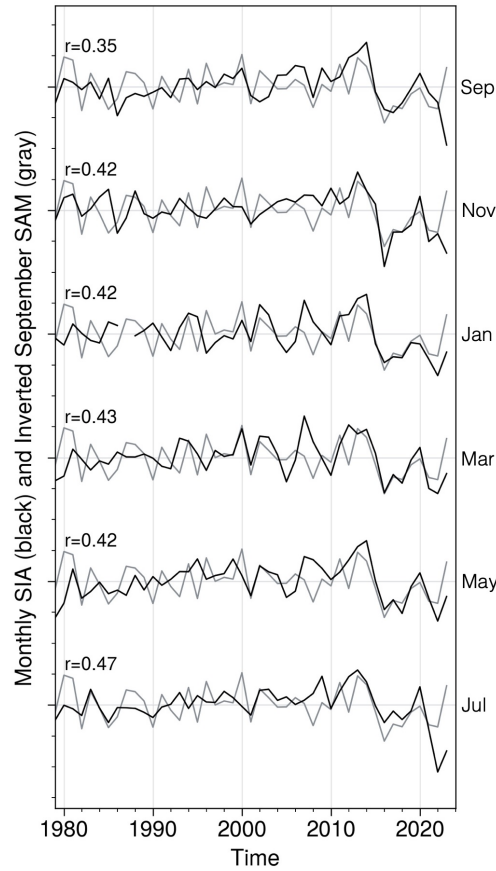


Figure 3.17: Time series of inverted and standardized September values of the Southern Annular Mode (SAM) index (gray) and standardized values of sea-ice area (SIA) anomalies as a function of month (black). That is: Each row shows the same September SAM index time series superposed on standardized values of SIA for the indicated months. The SAM index time series is inverted for the purpose of illustration. SIA time series for months January, March, May, and July are shifted by one year so that they align with the SAM index time series during the previous September. The correlation coefficients between each month of SIA and the inverted September SAM are labeled above each time series pair. All data are detrended with respect to the long-term mean climatology. Missing data in the January time series is explained in the Methods section. SIA months shown are chosen at 2-month intervals.

values of the SAM index; the black lines show SIA for the indicated months (months not shown in Figure 3.17 are shown in Figure 3.18).

The time series are standardized, and the SAM index is inverted so that negative values of the index indicate stronger than normal circumpolar westerlies, and vice versa. There is a clear visual relationship between September values of the SAM index and monthly SIA, not only for SIA values during September, but for SIA values during subsequent months as well.

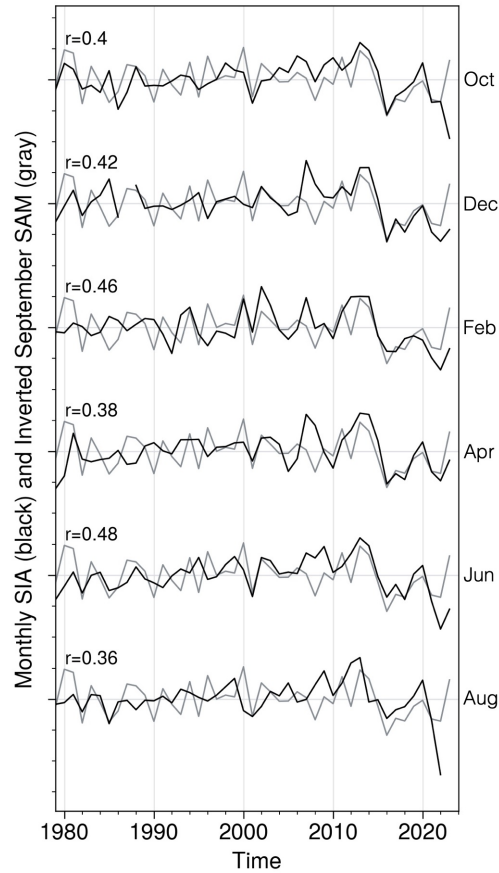


Figure 3.18: As in Figure 3.17, but for additional months not shown in Figure 3.17. SIA time series for months February, April, June, and August are shifted by one year so they align with the SAM index time series during the previous September. Correlation coefficients between each month of SIA and the inverted September SAM are labeled above each time series pair.

The linkages between September values of the SAM and SIA are particularly prominent over the past decade. The most notable exception arises in 2023, when sea-ice variability appears to follow variations in the SAM during the summer and autumn months, but not during the spring months of September–November (see also Purich and Doddridge 2023). It is worth noting that the key features of the seasonally-varying relationships between the SAM and SIA are reproducible in analyses limited to the period prior to the recent losses. For example, Figure 3.19 shows the same results as Figure 3.2b and Figure 3.13a, but for the period 1979–2015. Variations in the SAM during the sea-ice maximum have played an increasingly large role in annual-mean SIA over the past decade (compare Figure 3.13a and Figure 3.19b), but the general pattern of the seasonally-

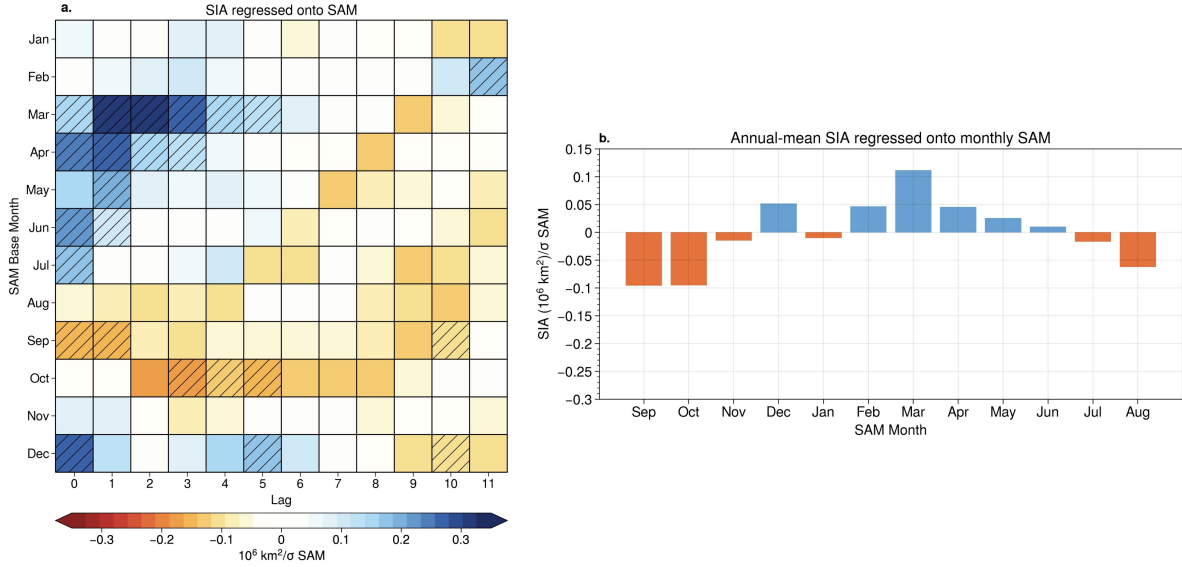


Figure 3.19: As in Figure 3.2b and Figure 3.13a, but for data limited to the period 1979–2015.

varying relationships between the SAM and SIA are recovered in analyses based on both the full and earlier periods of record.

3.3.3 Reproducibility in a climate model

We close the results by exploring the ability of the CESM2 climate model to reproduce the observed relationships. Figure 3.20 is an analogous figure to Figure 3.2b but for the 11-member ensemble mean of output from CESM2 run under CMIP6 historical forcings. Similarly, Figure 3.21 is also an analogous figure to Figure 3.2b but for each member of the 11-member ensemble. Within the CESM2 historical run, there are clear positive correlations between the SAM and SIA during the sea-ice maximum and negative correlations during the sea-ice minimum. The amplitude of the linkages is slightly smaller than those found in Figure 3.2b. There is notable variability amongst the ensemble members, with some ensemble members exhibiting more persistence of the SIA-SAM linkages during the sea-ice minimum and others exhibiting more persistence during the sea-ice maximum. Importantly, there are a couple of ensemble members that show a very similar pattern of results as the observations, indicating that the pattern from the observational results falls within the ensemble mean.

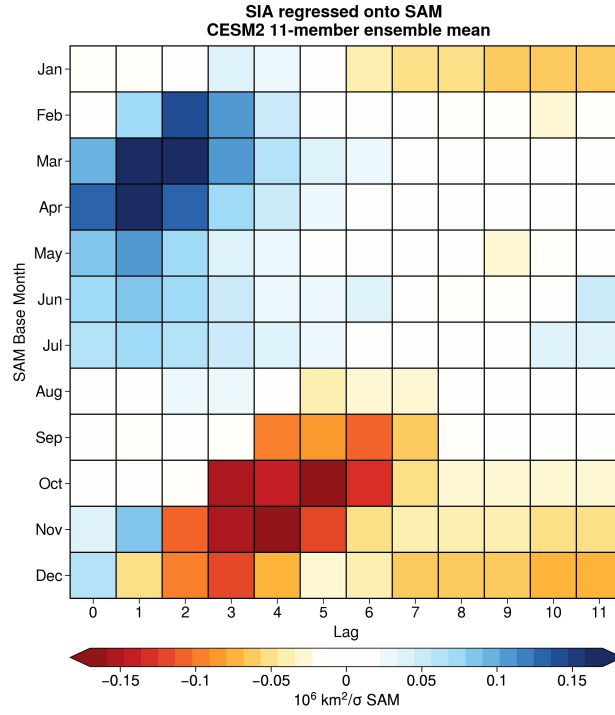


Figure 3.20: As in Figure 3.2b but with CESM2 run under CMIP6 historical forcing from 1850–2015. Results are showing the ensemble mean of the 11-member ensemble. Regression coefficients are calculated for each ensemble member before the ensemble mean is calculated.

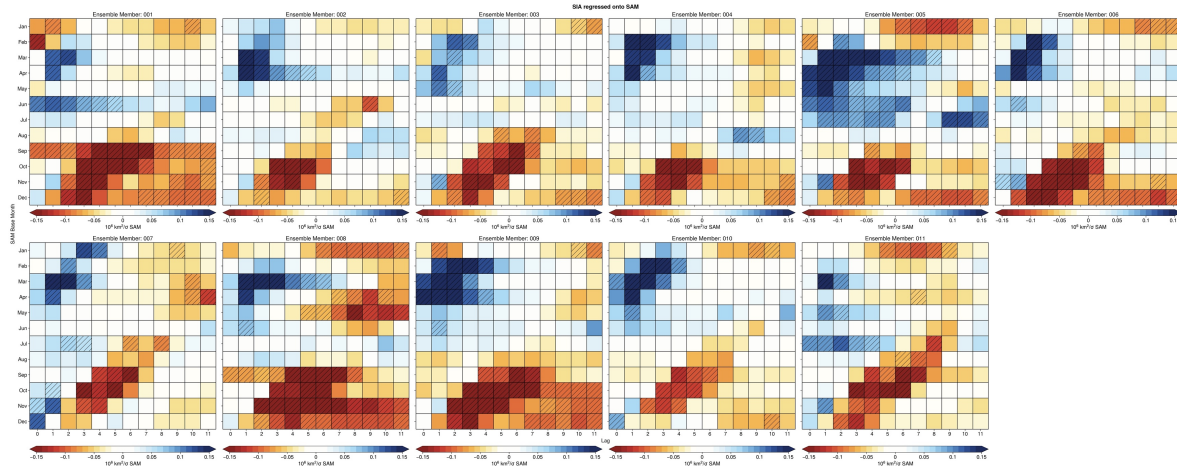


Figure 3.21: As in Figure 3.2b but with CESM2 run under CMIP6 historical forcing from 1850–2015. Each panel shows results for a different ensemble member that was part of the 11-member ensemble.

Figure 3.22 shows results analogous to Figure 3.2b for numerical output from CESM2 run under CMIP6 historical and SSP5-8.5 forcings. During the 20th century (Figure 3.22a,b), there is a clear positive correlation between the SAM and SIA during the sea-ice maximum and a clear negative correlation during the sea-ice minimum. As is the case in the observations, the linkages between the SAM and SIA during the sea-ice maximum exhibit more persistence than those during the sea-ice minimum. The simulated linkages have slightly weaker amplitudes compared to observations and peak at slightly different lags (note the colorbar range differences between Figure 3.2b and Figure 3.22a,b). During the 21st century (Figure 3.22c,d), the linkages become increasingly weak, consistent with predicted decreases in sea-ice coverage (Figure 3.22e). The broad similarities between the observed and simulated seasonally-varying relationships during the historical period are encouraging, given known biases in models' representations of the linkages between the atmospheric circulation and Antarctic sea ice (Roach et al. 2020; Wills et al. 2022). Future changes in the linkages between the SAM and sea-ice extent were also explored in Morioka et al. (2024), who found stronger linkages as anthropogenic forcing increases. However, their results are primarily based on annual-mean and contemporaneous correlations, which highlights the importance of the seasonally-varying lagged analysis applied here.

3.4 Discussion

Antarctic SIA has exhibited marked declines over the past decade. Several previous studies have probed the role of the atmosphere on the initial declines in sea ice in 2016 (Turner et al. 2017; Schlosser et al. 2018; Meehl et al. 2019; Ionita 2024; Jena et al. 2024). But the sustained losses over the past decade have been primarily linked to ocean warming (Meehl et al. 2019; Zhang et al. 2022; Purich and Doddridge 2023; Jena et al. 2024; Espinosa et al. 2024; Hobbs et al. 2024). The SAM, in particular, is thought to have played a largely negligible role in the decreases in SH-mean SIA over the past decade (Polvani et al. 2021; Purich and Doddridge 2023).

The results shown here highlight a key but seemingly overlooked contribution of the SAM to recent changes in SIA. The linkages arise not from the contemporaneous relationships between the

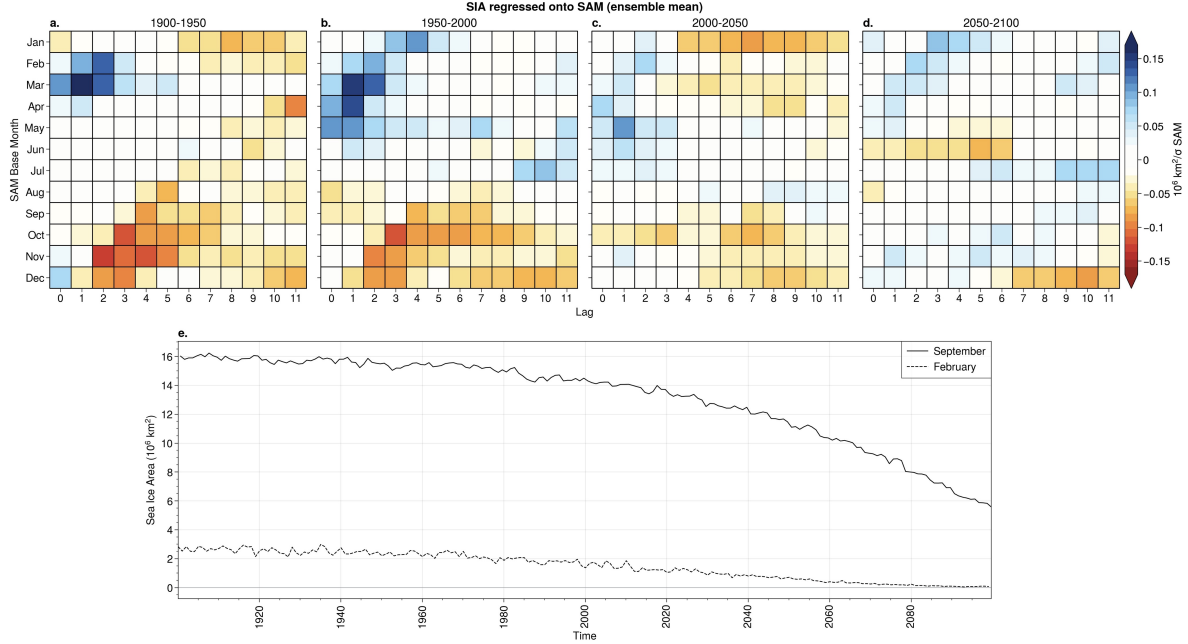


Figure 3.22: The relationship between sea-ice area and the Southern Annular Mode in CESM2. (a-d) As in Figure 3.2b, but for results based on ensemble mean output from CESM2 for the periods indicated. Results are formed for individual ensemble members and then averaged over all ensembles. All output is detrended over the indicated periods. (e) Time series of September and February sea-ice area (SIA). SIA used in time series is neither detrended nor deseasonalized. Output from 1900–2015 is derived from the historical simulation; output from 2015–2100 is derived from the SSP5-8.5 simulation. See the main text and Methods for details.

SAM and SH-mean SIA, but rather from the marked persistence of sea-ice anomalies induced by the SAM during the sea-ice maximum centered around September. The central findings include the following:

1. The linkages between the SAM and SH-mean SIA vary in both amplitude and sign from one season to the next (Figure 3.2b). The most prominent relationships between the SAM and SH-mean SIA arise during the sea-ice maximum and sea-ice minimum: Positive anomalies in the SAM are associated with hemispherically-averaged increases in SH sea ice during the sea-ice minimum, but hemispherically-averaged decreases during the sea-ice maximum.
2. Following the sea-ice minimum, SAM-induced anomalies in sea-ice decay after roughly ~ 4 months. But following the sea-ice maximum, SAM-induced anomalies in sea ice persist for up to a year. As such, SAM-induced anomalies in sea ice during the sea-ice maximum have

an outsized influence on annual-mean SIA. The large persistence in SAM-induced sea-ice anomalies following the sea-ice maximum is consistent with spring/summer feedbacks from both the SW clear-sky fluxes and potentially changes in ocean heat content (Figure 3.4 and Figure 3.6).

3. A notable component of the recent declines in SH-mean SIA are consistent with large variations in the SAM during the late winter/early spring season (Figure 3.13b, Figure 3.17).

The results shown here highlight the key role of the SAM during the sea-ice maximum in driving year-round changes in SH SIA. We have focused on September since it corresponds to a) the central month of the sea-ice maximum (Figure 3.2c), b) the month during which the SAM exhibited particularly large variability over the past decade (Figure 3.17), and c) the time of year when the SAM projects onto prominent persistence in SIA (Figure 3.2b). It is unclear what gives rise to the weaker relationships between the SAM and SIA prior to 2015 (Figure 3.19). Potential factors include weaker upper ocean warming prior to 2015, smaller amplitude variations in the SAM, and differences in the mean distribution of sea-ice thickness or concentration.

What physical processes underlie the large and exceptional variations in the SAM during September in the mid-2010s? Prior to 2016, the SAM exhibited large amplitude anomalies during the cold season months and late spring, but did not exhibit notable anomalies during September. The large amplitude of the SAM during September 2016 and the subsequent decrease in the index through 2017 are unmatched in the historical record (Figure 3.17). The variations arise too early in the year to be traced to stratospheric ozone depletion (e.g., Polvani et al. 2021), and they are not coincident with large anomalies in the SH stratospheric vortex. The unusual variations in the SAM during the sea-ice maximum during the mid-late 2010s may have arisen from a variety of processes, including, for example, atmosphere/ocean interactions, coupling with the stratosphere, the remote response to tropical variability, or simply internal variability in the extratropical atmosphere. The relative contributions of various physical processes to variations in the SAM during the sea-ice maximum remain to be determined.

Chapter 4

An Observational Analysis of the Impact of Antarctic Sea-Ice Loss on Regional Changes in the Atmospheric Circulation

4.1 Introduction

Antarctic sea ice has experienced unprecedented decline over the past decade (Purich and Doddridge 2023). As discussed in Chapter 1, a large body of work has been dedicated towards trying to understand the causes of such decline (e.g., Meehl et al. 2019; Turner et al. 2022; Purich and Doddridge 2023; Espinosa et al. 2024), with few studies focused on potential implications from the recent changes. Similarly, there is a large body of research dedicated to understanding the impacts of Arctic sea-ice loss (e.g., Deser et al. 2010; Screen and Simmonds 2010a,b; Blackport and Kushner 2017; Sun et al. 2018; Zappa et al. 2018; Screen and Blackport 2019; Smith et al. 2022), but not Antarctic sea-ice loss, perhaps because the Arctic has experienced sea-ice loss across much of the observational record (Roach and Meier 2024). While some similarities in the impacts of Arctic versus Antarctic sea-ice loss are expected, the contrasting geography and the subsequent differences in seasonal cycle strength (Roach and Meier 2024) warrant treating each region individually. Thus, it is critical to investigate sea-ice loss impacts specifically in the Antarctic, especially in light of recent changes. Chapter 3 was focused on the influence of the atmosphere on Antarctic sea ice, whereas in this chapter, we focus on the influence of Antarctic sea ice on the atmosphere.

Of the studies focused on potential impacts of Antarctic sea-ice loss, most of them are modeling studies, using both atmosphere-only and fully coupled models. These studies have identified impacts such as shifts in the stormtracks (Menéndez et al. 1999; Bader et al. 2013; England et al. 2018), an increase in heat flux into the atmosphere and a resulting increase in precipitation (Wang

et al. 2020), and a weakening polar stratospheric vortex (Rea et al. 2024; Song et al. 2025). Work using fully coupled models has found that impacts extend outside of the high latitudes, including enhanced warming in the tropical Pacific (England et al. 2020b; Ayres et al. 2022), an equatorward intensification of the Intertropical Convergence Zone (England et al. 2020b), and even enhanced Arctic sea-ice loss resulting in warming and freshening of the Arctic Ocean (England et al. 2020a; Ayres et al. 2022). The few observational studies that have focused on this topic have found two-directional coupling between stormtracks and sea-ice loss (Zhang et al. 2024), impacts from sea-ice loss on precipitation over the Antarctic ice sheet (Kromer and Trusel 2023), and substantial heat loss from the ocean to the atmosphere, resulting in increased storminess (Josey et al. 2024).

To our knowledge, there has not been an observationally-based study providing an estimate of the impact of sea-ice loss on the local atmosphere across the observational record and across the entire Antarctic sea-ice region. The observational studies cited above either focused on a particular region/time period (Kromer and Trusel 2023; Josey et al. 2024) or were more focused on the impacts on large-scale atmospheric circulation as opposed to local covariability between sea ice and atmospheric changes (Zhang et al. 2024). Negative sea-ice anomalies during winter have become more common in recent years (Roach and Meier 2024). Josey et al. (2024) highlighted the large increase in heat flux into the atmosphere from winter sea ice decline, motivating the need for an estimate based on the current observational record of the impact of sea-ice loss on heat fluxes, precipitation, and cloud cover that can be compared to model results. Such an estimate is important to understand the current impact of sea-ice loss as well as potential biases in model output and the observationally-constrained datasets. Although reanalysis and satellite data are not pure observations, they provide the best spatial and temporally continuous observational estimate available, even while taking into account their biases.

This work uses a novel technique of gridpoint-by-gridpoint regression analysis to analyze the impacts of sea-ice loss across the observational period and compare the results to sea-ice forced atmosphere-only simulations and fully-coupled high-resolution modeled historical simulations. This technique was recently utilized by Larson et al. (2024) to investigate the impacts of SST vari-

ability in the western boundary currents on climate variability. They showed that this local-local regression technique can help isolate the fine-scale covariability between SSTs and atmospheric variability. We extend this technique to isolate the fine-scale covariability between Antarctic sea ice and atmospheric variability.

In addition to providing a method for creating an observational estimate of the atmospheric impacts of Antarctic sea-ice loss, this regression analysis and subsequent comparison with models allow us to isolate the impacts from different mechanisms by which sea ice could impact the local precipitation variability. It has been shown that sea-ice loss increases turbulent heat flux into the atmosphere, inducing localized warming and impacting temperature gradients (e.g., Screen and Simmonds 2010a; Ayres et al. 2022; Josey et al. 2024). Thus, there are three primary ways that sea-ice loss could affect local precipitation variability. 1) Sea-ice loss increases local turbulent heat flux into the atmosphere, increasing vertical motion and precipitation over the same regions (e.g., Josey et al. 2024). 2) Sea-ice loss increases local turbulent heat flux and vertical mixing, mixing free tropospheric winds to the surface, resulting in horizontal convergence and increased precipitation downwind of the regions of sea-ice loss. This mechanism has been used previously to explain the connection between western boundary currents and the atmospheric circulation (e.g., Chelton et al. 2004; Minobe et al. 2008; Minobe et al. 2010). 3) Sea-ice loss alters the near-surface temperature gradient, changing the atmospheric baroclinicity, and resulting in an equatorward shift of the stormtracks and associated precipitation (e.g., Hoskins and Valdes 1990; Butler et al. 2010; Baker et al. 2017). Ayres et al. (2022) and England et al. (2018) showed that Antarctic sea-ice loss results in increased precipitation via this third mechanism. Our analysis technique provides a unique opportunity to isolate the relative impacts from each of these mechanisms and their importance to future precipitation changes. While the first and third mechanisms have been investigated in previous studies on Antarctic sea-ice loss, the second mechanism has not.

Here we provide observational insights into the impact of Antarctic sea-ice loss on regional changes in the atmospheric circulation using a gridpoint-by-gridpoint regression analysis. We show that given a decrease in Antarctic sea ice, there is a resulting increase in turbulent heat

flux (THF), precipitation rate, cloud fraction, surface winds, and temperature in the same regions. These changes in the atmosphere are most pronounced during the winter season and are a considerable portion of the climatological variability. This same covariability is also apparent in sea-ice forced atmosphere-only simulations, with a similar magnitude as the observationally-based results. Finally, we demonstrate the portion of atmospheric changes that can be attributed to the regional covariability with sea-ice loss versus the more remote relationships. Section 4.2 begins by outlining the data and methods used in the study. Section 4.3 outlines the results of this study, and Section 4.4 provides additional discussion and conclusions about this work.

4.2 Data and Methods

4.2.1 Observationally-Constrained Data

Monthly sea-ice concentration (SIC) data are from the NOAA/NSIDC Climate Data Record of Passive Microwave Sea Ice Concentration, Version 4 (Meier et al. 2021a), and covers the period January 1979–July 2024. Cloud fraction data is from the CERES-EBAF Edition 4.2 top-of-atmosphere data product (Loeb et al. 2018). This monthly data covers the period March 2000–July 2024. Cloud fraction is reported as the fraction of each grid cell covered by clouds. All other monthly atmospheric data are from ERA5 with a spatial resolution of 25 km x 25 km (Hersbach et al. 2020). Turbulent heat fluxes are shown with a sign convention of positive up. We use the terms observational or observationally-constrained data interchangeably in this chapter while recognizing that the observational data we use is not pure observations. Additional details about these datasets can be found in Chapter 2.

4.2.2 Model Output

We use two atmosphere-only simulations forced with different states of sea ice. The first set of simulations we will call the transient SIC simulations are forced with the 1978–2019 time series of SIC from HadISST (Rayner et al. 2003). These simulations are run on CAM6 (Danabasoglu et al. 2020). Regression analysis is performed for each ensemble member first, then an ensemble mean

of regression coefficients was calculated. The second set of simulations we use are run according to the PAMIP protocol (Smith et al. 2019), on CESM2 (Danabasoglu et al. 2020) which also uses CAM6. The first experiment used is forced with preindustrial SIC, the second experiment used is forced with a future SIC state. Therefore, the difference between these two simulations isolates the impacts from a change in Antarctic sea ice between preindustrial and future periods. An ensemble mean was calculated prior to taking the difference between these two simulations. See Chapter 2 for more details on the setup of these simulations.

We utilize monthly-mean output from CESM-HR when comparing observationally-constrained and atmosphere-only simulation results to results using a fully-coupled model (Chang et al. 2020). We analyze the coupled historical high-resolution simulations across the period 1920–2005. These high-resolution simulations have an atmospheric resolution of 0.25° and an ocean resolution of 0.1° with 10 ensemble members. Similar to the transient SIC simulations, we perform regression analysis for each ensemble member and then take an ensemble mean of the regression coefficients. See Chapter 2 for additional details.

4.2.3 Analysis methods

Unless otherwise noted, the long-term linear trend and seasonal cycle are removed from all data prior to analysis. The long-term linear trend is calculated across the entire data record, with the exact period used depending on the length of each dataset. I.e., the base period for calculating the long-term linear trend is January 1979–July 2024 for ERA5 data, while it is March 2000–July 2024 for data from CERES. Results were often calculated as a function of season, where seasons were determined by the seasonal cycle of sea ice. Since the sea-ice maximum occurs in September and the sea-ice minimum occurs in February, the sea-ice maximum season was defined as August, September, and October. The sea-ice melting season was defined as November, December, and January. The sea-ice minimum season was defined as February, March, and April. The sea-ice growth season was defined as May, June, and July.

Unless otherwise noted, regressions and correlations are performed for each grid-point between the two variables. This treats each grid-point separately and allows the investigation of covariability of variables at a fine-spatial resolution. Additional details on the calculation of regression coefficients and significance testing can be found in Chapter 2.

4.3 Results

4.3.1 Local relationships in observational data

We begin our results by providing some additional motivation, looking at the pattern of variability within atmospheric variables from the observational data. Figure 4.1 shows the standard deviation of the climatological SIC, as well as turbulent heat flux (THF), precipitation rate, and cloud fraction for each season. The most variability in SIC occurs around the periphery of the sea-ice edge, expanding and contracting with the seasonal cycle. During the summer, the SIC variability is more dispersed, as the sea-ice pack melts and gets very close to the Antarctic continent. During the winter, the variability in SIC is more confined to the edge of the sea-ice pack.

The variability of THF has local maxima in regions where there is the most sea-ice variability. This indicates that sea-ice variability impacts the variability of THF through its role in the exchange of heat and moisture. There is a seasonality to the location of this variability, as the sea-ice pack retreats in the summer, but also to the amplitude of the variability, with less THF variability in the summer due to a smaller temperature gradient between the atmosphere and ocean. Cloud fraction and precipitation rate have a slightly different pattern of variability. The maximum cloud fraction variability is over the Antarctic continent, and the maximum variability over the ocean is in sea-ice-covered regions. This cloud fraction variability is not confined to the sea-ice edge region, like THF and SIC variability is. Precipitation rate has a more uniform pattern of variability, with maxima along the coasts of land masses, but no visual correlation with SIC variability.

Next, we look at seasonal variability in temperature and wind. Figure 4.2 illustrates the seasonal variability in 2-meter temperature, 10-meter wind speed, and 500 hPa temperature. The pattern of variability in 2-meter temperature is very similar to that of cloud fraction, with the largest

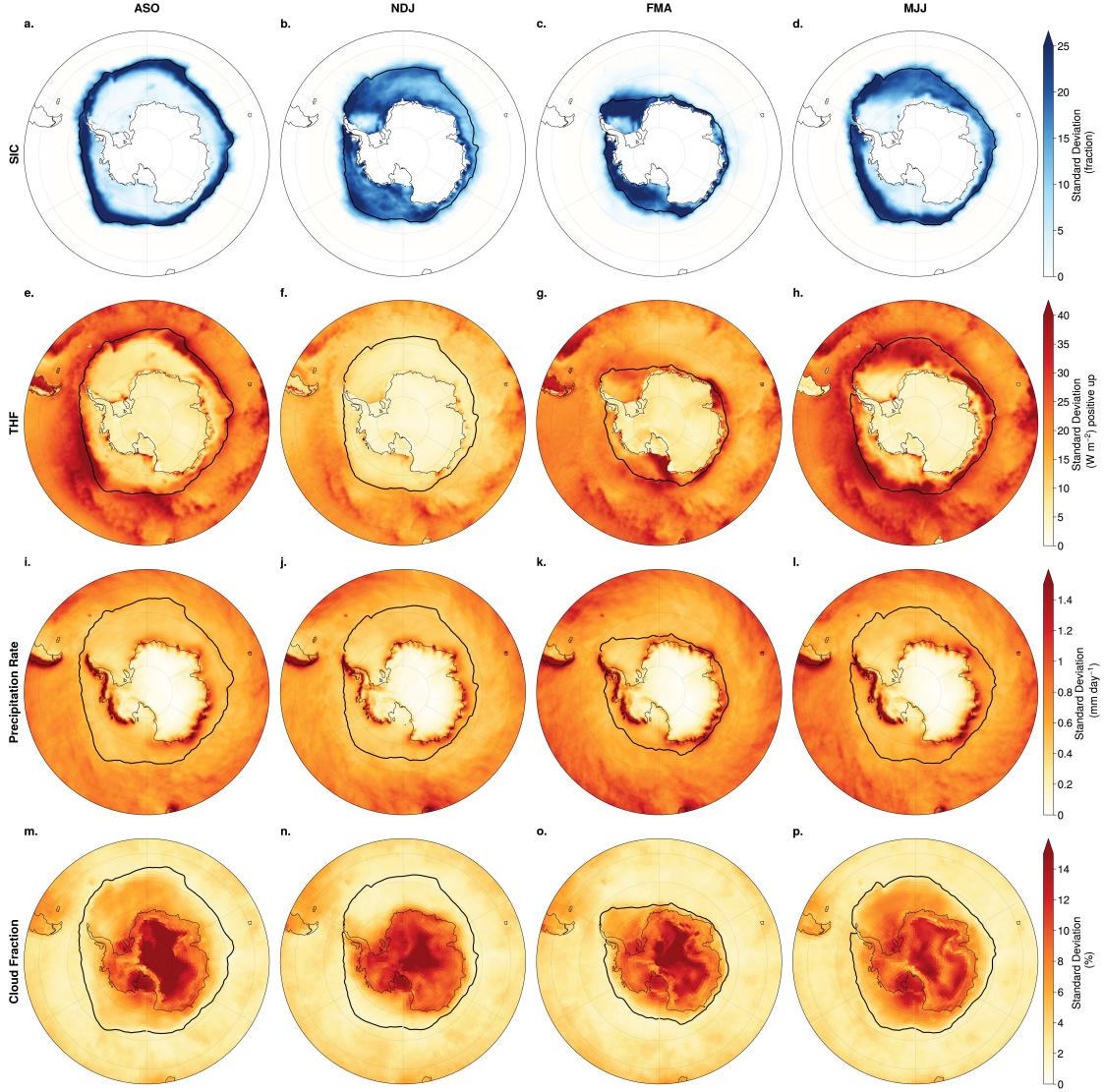


Figure 4.1: Standard deviation of (a-d) sea-ice concentration (SIC), (e-h) turbulent heat flux (THF), (i-l) precipitation rate, and (m-p) cloud fraction monthly anomalies across the observational record for each season. Each column is a different season, (a,e,i,m) is August, September, and October (ASO), (b,f,j,n) is November, December, and January (NDJ), (c,g,k,o) is February, March, and April (FMA), (d,h,l,p) is May, June, and July (MJJ). The black contour on each plot is the climatological sea-ice extent (SIE; i.e. the edge of where sea-ice concentration is at least 15%) for the corresponding season.

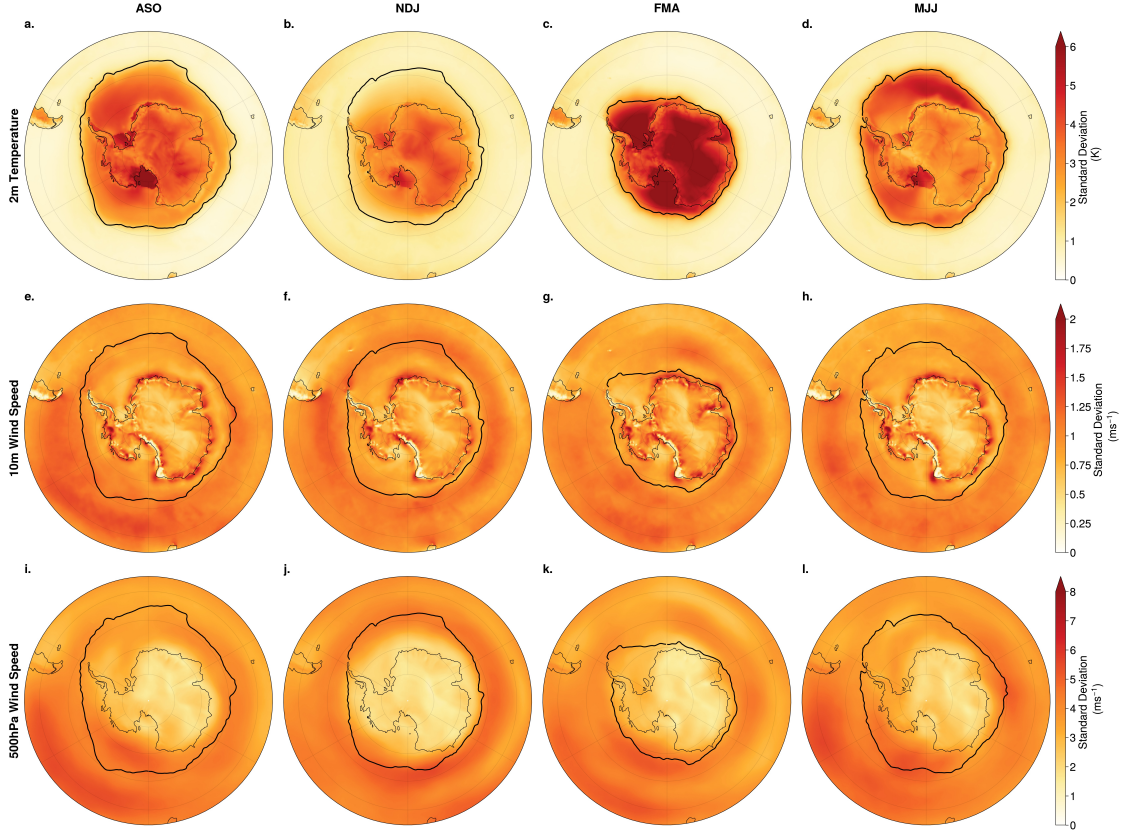


Figure 4.2: Standard deviation of (a-d) 2-meter temperature, (e-h) 10-meter wind speed, (i-l) 500 hPa wind speed monthly anomalies for each season. Each column is a different season, and the black contour is the climatological SIE, structured like Figure 4.1.

variability occurring over areas of sea ice. This pattern in 2-meter temperature is likely due to the localized warming or cooling that occurs from sea-ice freeze or melt (Serreze et al. 2009; Screen and Simmonds 2010a,b). 10-meter and 500 hPa wind speed variability have a relatively homogeneous pattern, similar to that of precipitation (compare Figure 4.2e-l and Figure 4.1i-l). 500 hPa wind speed has substantially more variability than 10-meter wind speed but has a similar pattern, with very slight maxima over regions of the storm tracks. There is a minimum in 500 hPa wind speed variability over the Antarctic continent that is not apparent for 10-meter wind speed, likely a result of storm tracks dominating the wind speed variability at higher levels of the troposphere.

Figure 4.1 and Figure 4.2 clearly show the visual correlation between sea-ice variability and aspects of atmospheric variability within observations. Some of these relationships have been explored in prior work (England et al. 2018; Ayres et al. 2022; Josey et al. 2024; Zhang et al. 2024),

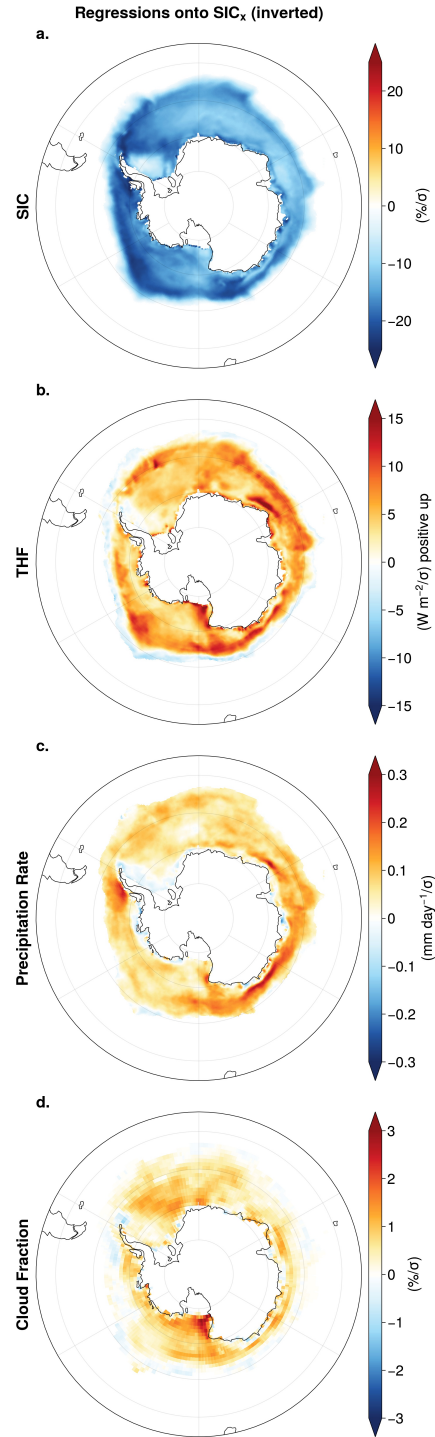


Figure 4.3: Maps of regression coefficients from (a) SIC, (b) THF, (c) precipitation rate, (d) cloud fraction regressed onto standardized inverted SIC. Regressions are computed across all months across the entire observational period.

but the lack of previous observation-based studies and the clear relationships shown here motivate further exploration. Figure 4.3 shows the results of SIC, THF, precipitation rate, and cloud fraction regressed onto standardized inverted SIC, using the gridpoint-by-gridpoint regression analysis. These regressions are computed at the gridpoint level, so each gridpoint is treated separately and has its own regression coefficient. Regressions are done onto *inverted* SIC, so the interpretation is the response to sea-ice *loss*. A positive regression coefficient indicates an increase in the dependent variable given a decrease in sea ice.

Figure 4.3a is equivalent to the standard deviation of SIC and is thus comparable to an all-months version of Figure 4.1a-d. It highlights that even across all months, there is considerable variability in SIC. Figure 4.3b shows that a decrease in sea ice leads to an increase in THF from the ocean into the atmosphere. This is consistent with prior studies (England et al. 2018; Ayres et al. 2022; Josey et al. 2024; Zhang et al. 2024) and with temperature/moisture differentials between the ocean and atmosphere. The components of THF are latent and sensible heat fluxes, which are dependent on moisture and temperature differentials, respectively, between the surface and the atmosphere. When sea-ice loss occurs, the open ocean is exposed, which has a larger temperature/moisture differential with the atmosphere than between sea ice and the atmosphere.

A similar relationship is present in Figure 4.3c and d with precipitation and cloud fraction. Given sea-ice loss, there is a positive correlation with precipitation rate and cloud fraction. The patterns of regression of the three atmospheric variables are broadly uniform across areas of sea-ice loss, and their responses are consistent with established atmospheric dynamics. An increase of THF into the atmosphere is expected to enhance vertical motion, leading to increased precipitation and cloud cover. The consistency of the results of Figure 4.3 with established atmospheric dynamics, together with the widespread agreement across regions of sea-ice loss, indicates a robust signal.

It is important to note that Figure 4.3 shows regression coefficients computed across all months of the record, not taking seasonality into account. Prior work has shown that there is a seasonality in the response of the atmosphere to sea-ice loss (e.g., England et al. 2018; Ayres et al. 2022).

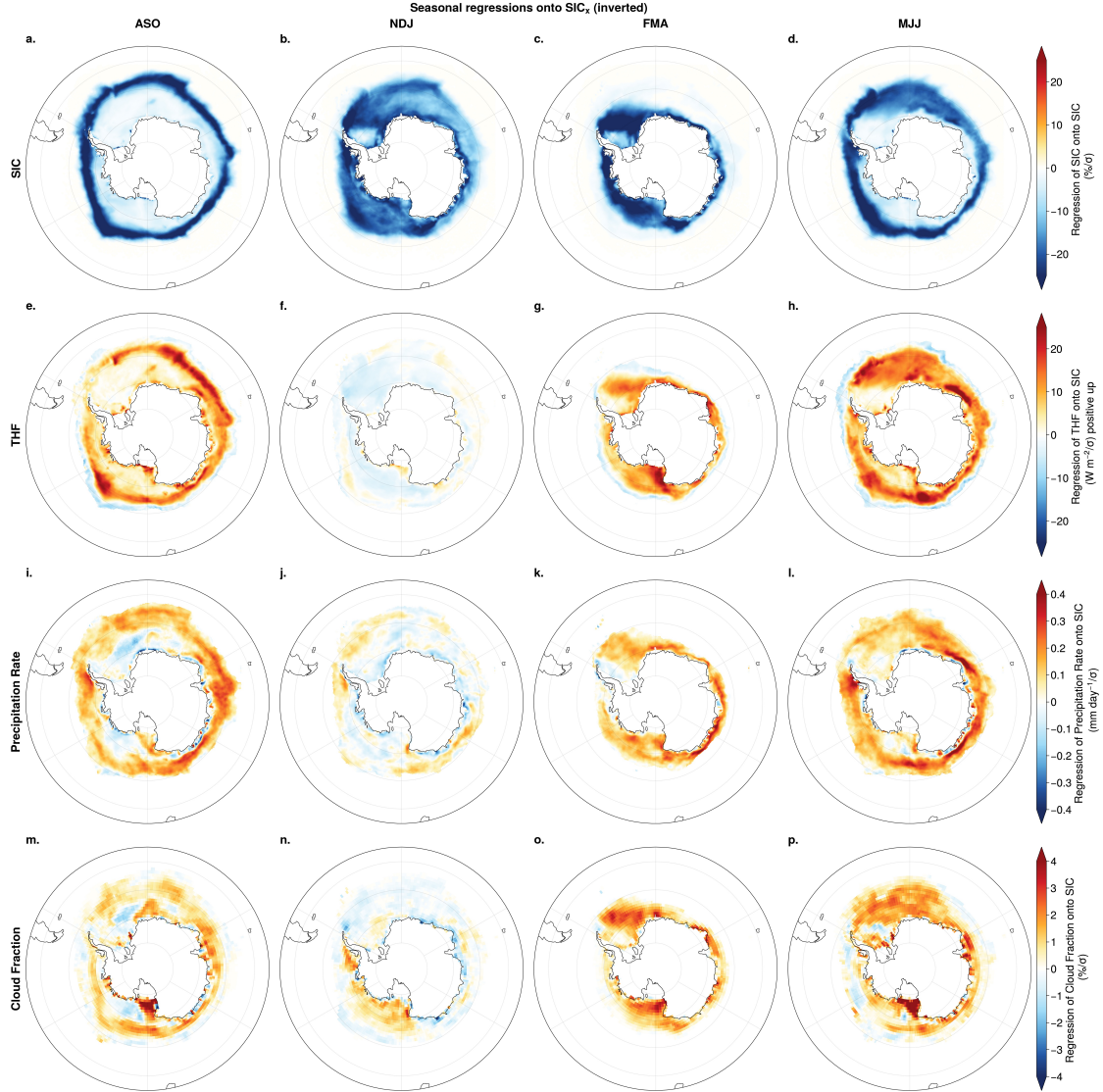


Figure 4.4: As in Figure 4.3 but split up by season. (a-d) SIC, (e-h) THF, (i-l) precipitation rate, (m-p) cloud fraction regressed onto standardized inverted SIC. Regressions are computed for each season, with each column showing results from each season.

Figure 4.4 probes that result within this observational data. Figure 4.4 shows regression coefficients from the regression of SIC, THF, precipitation rate, and cloud fraction maps onto standardized inverted SIC maps.

Similar to Figure 4.3a, the top row of Figure 4.4 is equivalent to the standard deviation of SIC, this time broken up by season. This means that the top row of Figure 4.4 is identical to the top row of Figure 4.1. We reemphasize that the most SIC variability occurs near the perimeter of the sea-ice pack, and expands/contracts with the seasonal cycle. Rows 2–4 of Figure 4.4 show a similar

relationship between sea-ice loss and the atmospheric variables as in Figure 4.3 but with a distinct seasonality. The strongest relationships between THF, precipitation rate, and cloud fraction with SIC loss occur in the cold-season months of May-October, with substantially weaker relationships during the summer months.

The seasonality of these relationships with sea-ice loss has been noted before in Antarctic sea-ice literature (England et al. 2018; Ayres et al. 2022) but not in observational data. This seasonality can be attributed to the seasonality of the temperature differential between the ocean and the lower atmosphere, similar to THF variability. When sea-ice loss occurs in the winter, a relatively warm ocean is exposed to very cold air, resulting in a large increase in THF into the atmosphere. This increase in heat in the atmosphere drives a stronger response in precipitation and cloud fraction during the austral winter months. Recently, there has been an increasing number of sea-ice anomalies occurring during the winter months (Roach and Meier 2025). The results from Figure 4.4 indicate that there is thus an increasing potential for impact on the local atmospheric conditions.

All three variables exhibit a broadly uniform pattern of positive correlations with sea-ice loss, with particularly strong responses near the Antarctic Peninsula, in the Indian/Pacific Ocean sector, and in the Ross Sea. All of these regions experience increases in THF upwards of $20 \text{ Wm}^{-2}/\sigma$, precipitation rate of $0.4 \text{ mm day}^{-1}/\sigma$, and cloud fraction of about $3 \text{ } \%/ \sigma$. To put these numbers into context, the standard deviation in similar regions of THF is $35\text{--}40 \text{ Wm}^{-2}$, precipitation is 0.8 mm day^{-1} , and cloud fraction is $7\text{--}8\%$ (Figure 4.1). Thus, a one sigma change in sea ice could result in a $\sim 50\text{--}60\%$ increase in THF and precipitation, and a 40% increase in total cloud cover.

The significance of these relationships is quantified in Figure 4.5. This figure is structured the same way as Figure 4.4 with each row showing the correlation between a different atmospheric variable and sea-ice loss, and each column showing correlations for a different season. Stippling in Figure 4.5 indicates correlations that are statistically significant at the 95% confidence level. There are many areas with a statistically significant correlation with sea-ice loss. The regions from Figure 4.4 with the largest regression coefficients also have significant correlation coefficients.

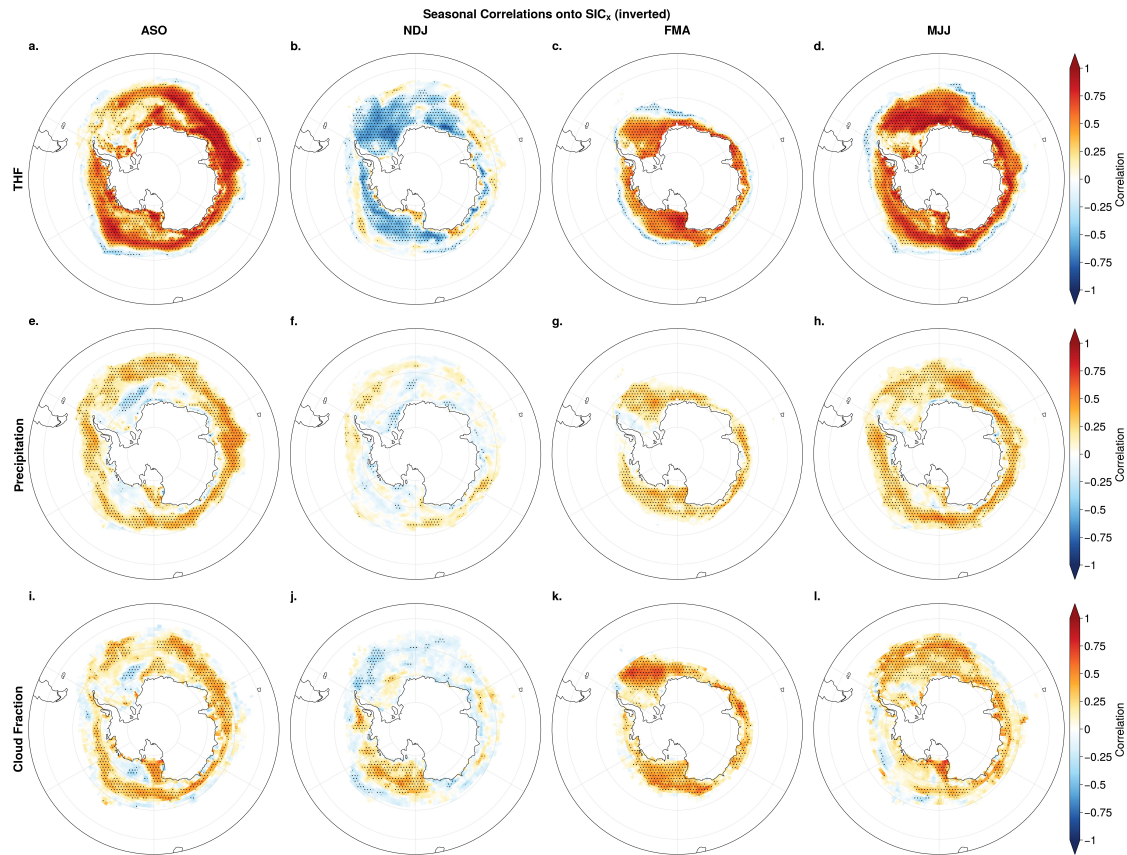


Figure 4.5: Correlations between inverted SIC and (a-d) THF, (e-h) precipitation rate, and (i-l) cloud fraction, discretized by season. Each column shows the result from a different season. Stippling indicates statistically significant correlations at the 95% confidence interval.

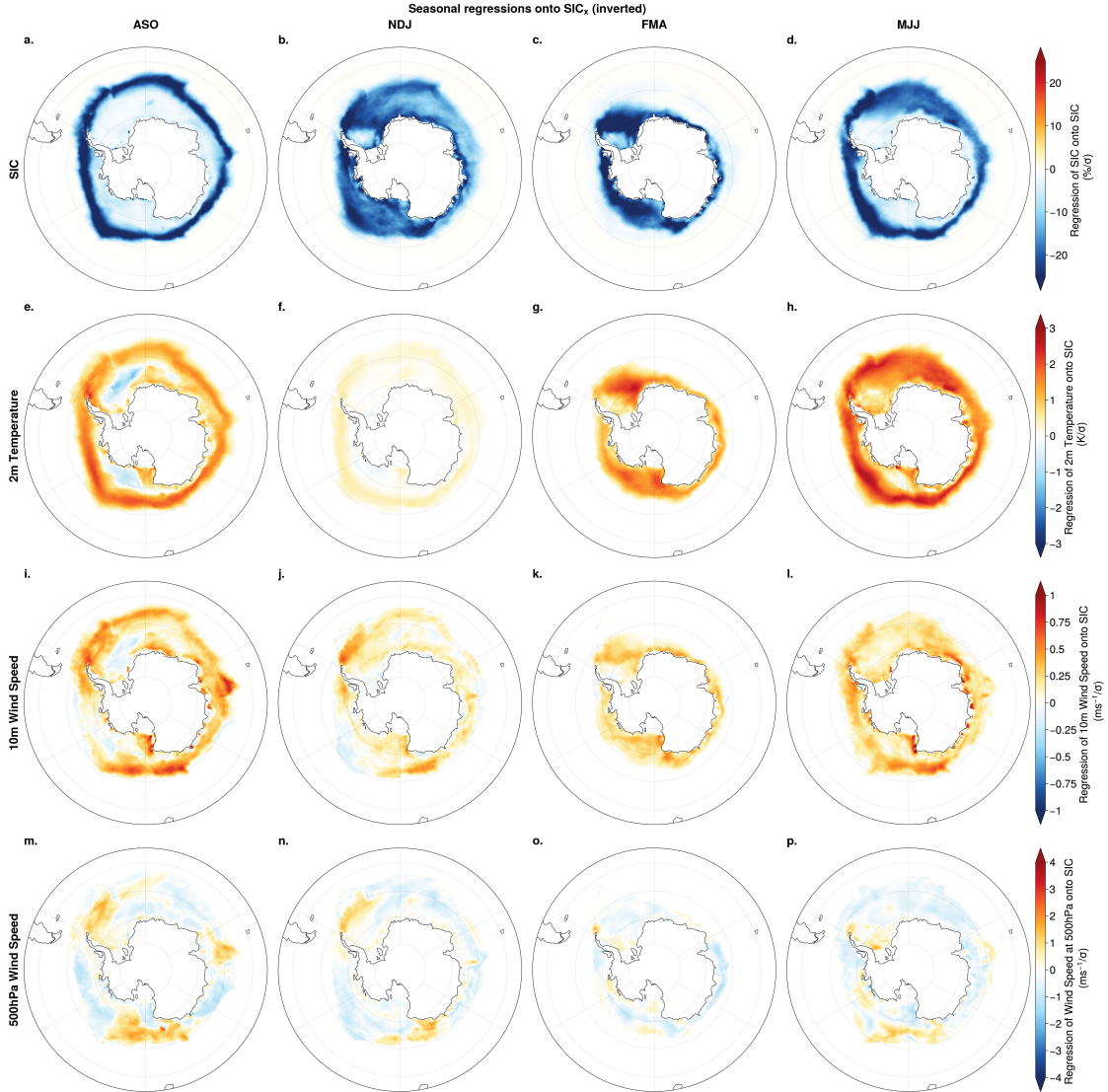


Figure 4.6: As in Figure 4.4 but for regressions of 2-meter temperature, 10-meter wind speed, and 500 hPa wind speed onto standardized inverted SIC loss.

Next, we perform a similar regression analysis for additional atmospheric variables, namely, 2-meter temperature, 10-meter wind speed, and 500 hPa wind speed (Figure 4.6). There is a clear positive correlation between near-surface temperatures and wind speeds with sea-ice loss (see rows two and three of Figure 4.6). Similar areas in Figure 4.6 as in Figure 4.4 exhibit the strongest signal: in general, along the periphery of the sea-ice pack, and smaller regions near the Antarctic peninsula, Ross Sea, and Indian/Pacific Ocean sectors. These smaller local maxima are particularly apparent in the regression with 10-meter wind speed. 500 hPa wind speed regressed

onto sea-ice loss exhibits a weaker relationship. Note that although the regression coefficients of 500 hPa wind speed are larger than those for 10-meter wind speed (compare colorbar of rows three and four in Figure 4.6), they are less meaningful once the inherent variability of 500 hPa wind speed is considered (see Figure 4.2). The colorbars of Figure 4.6 are scaled such that the maximum and minimum values are about 50% of the standard deviation amplitudes from Figure 4.2. This way, it is visually easier to see the impact such relationships would have on the variability.

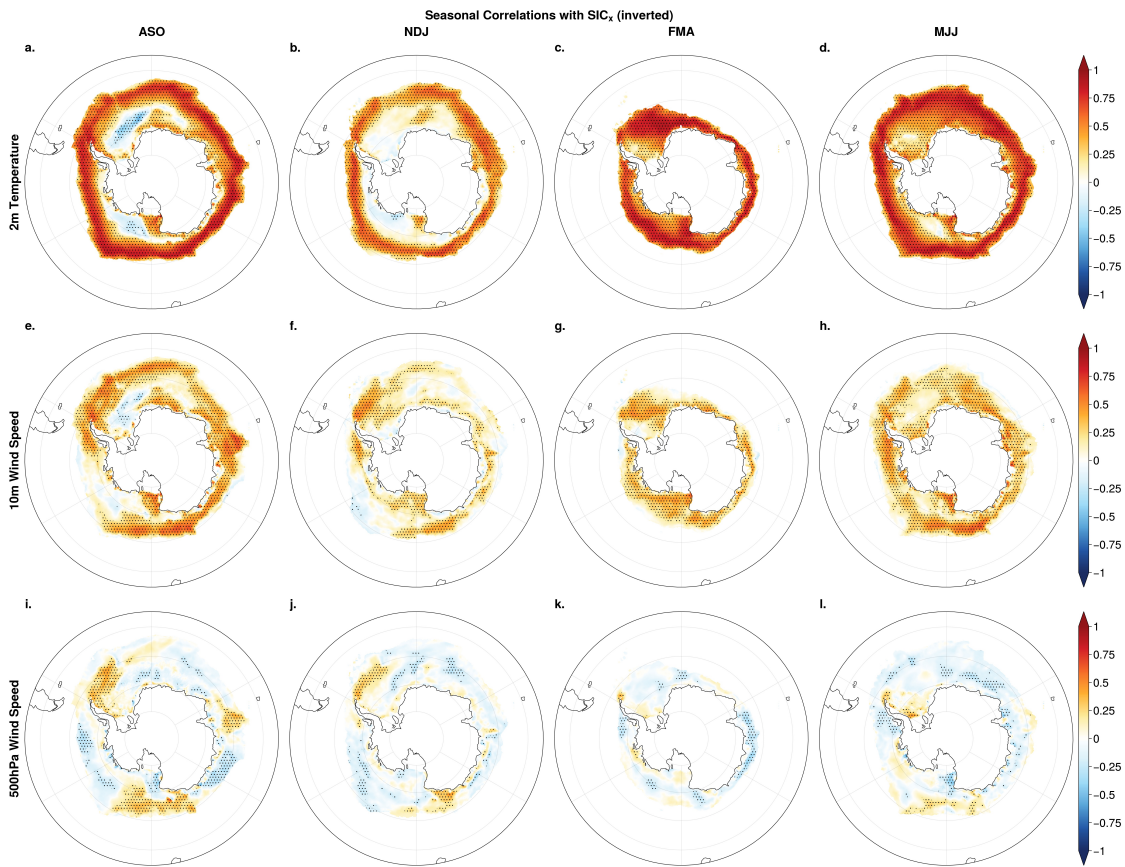


Figure 4.7: As in Figure 4.5 but for (a-d) 2-meter temperature, (e-h) 10-meter wind speed, (i-l) 500 hPa wind speed.

Another way to look at this is to look at the correlations of these three variables and sea-ice loss (Figure 4.7). This figure shows the correlations of 2-meter temperature, 10-meter wind speed, and 500 hPa wind speed with SIC loss, similar in structure to Figure 4.5. Stippling in Figure 4.7 indicates statistical significance of the corresponding correlations. The variables that have the strongest

relationship with SIC loss are 2-meter temperature and 10-meter wind speed. Correlations of both 2-meter temperature and 10-meter wind speed with SIC loss are widely significant across the regions of sea-ice loss. 500 hPa wind speed has a much weaker relationship with SIC loss, with only a couple of small areas exhibiting statistically significant correlations.

Figure 4.6 and Figure 4.7 indicate that this gridpoint-by-gridpoint regression analysis can isolate one of the three ways that sea-ice loss impacts precipitation (as outlined in the Introduction). Figure 4.6 and Figure 4.7 show an increase in near-surface temperature and wind speed given sea-ice loss, which is indicative of increased mixing of stronger free tropospheric winds down to the surface from an increase in THF and vertical motion. Since this signature does not extend to the higher levels of the atmosphere in this methodology (see row four of Figure 4.6), our observational results indicate that these local relationships are not a result of large-scale increases in wind speed, but rather are from mixing of higher-level winds to the surface. It is important to note that these increases in near-surface wind speed could be partially due to a decrease in surface roughness from the transition of sea ice to ocean surface (Mioduszewski et al. 2018; DuVivier et al. 2023). However, the seasonality we see in the response indicates that there are additional mechanisms responsible for the increased wind speeds.

The results of this chapter clearly show a robust relationship between sea-ice loss at the gridpoint scale and increases in heat flux, cloud fraction, precipitation rate, and near-surface temperature/winds across much of the sea-ice-covered regions.

4.3.2 Temperature responses at upper-levels

So far, results have only been shown for near-surface or single-leveled variables. Given the implications for large-scale circulation, it is important to understand how changes in sea ice could influence upper levels of the troposphere, outside of 500 hPa wind speed.

Figure 4.8 explores how the response of temperature to sea-ice loss changes at different levels of the atmosphere. For simplicity, we only show results from the August, September, and October season, but the results for other seasons follow the established seasonality. Maps of the regression

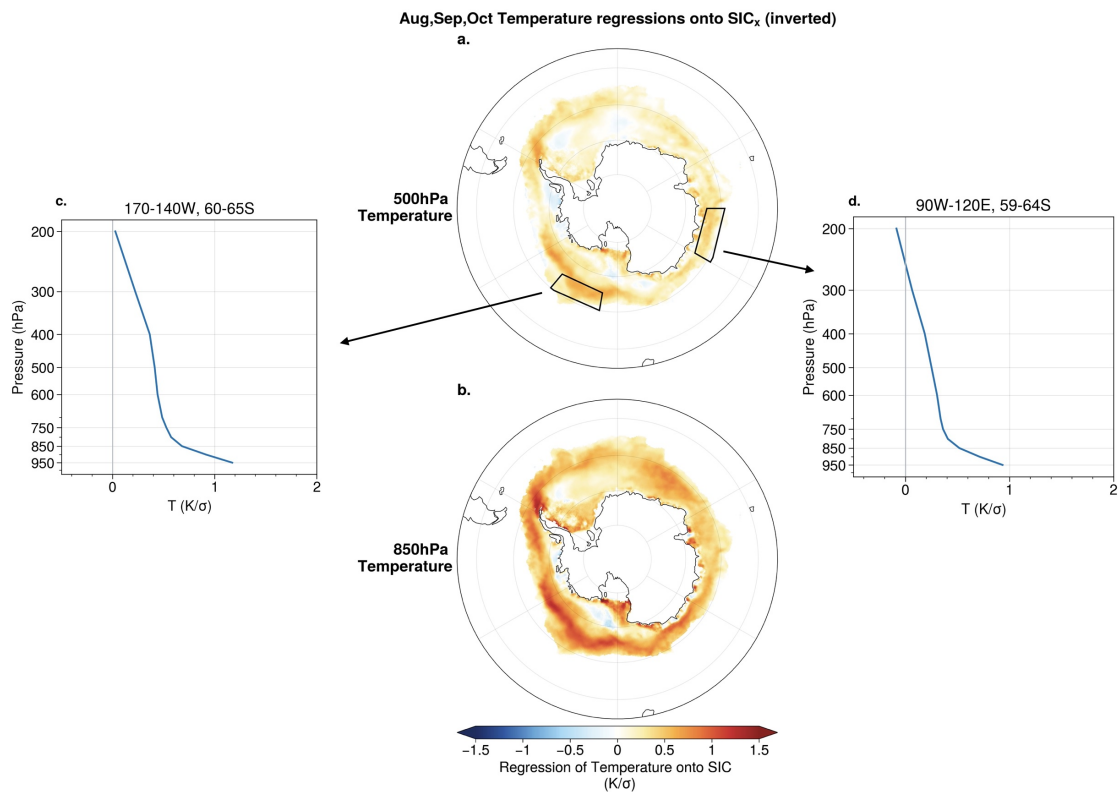


Figure 4.8: Regression of August, September, and October seasonal mean regression of (a) 500 hPa and (b) 850 hPa temperature onto standardized inverted SIC. (c,d) Vertical profile of area-averaged regressions of temperature onto standardized inverted SIC. Regions that are area-averaged are indicated with black boxes in (a), with arrows pointing to the corresponding vertical profile. Latitude and longitude bounds of the area averages are indicated in the titles of (c) and (d).

of 500 hPa and 850 hPa temperature onto the sea-ice loss show a clear temperature response that extends into the free troposphere, and is not confined to the surface. Prior work has concluded that the response to Antarctic sea-ice loss is vertically confined to lower levels of the atmosphere (England et al. 2018). We find the largest response is closest to the surface (Figure 4.6e-h) and lower levels of the atmosphere (Figure 4.8b), but there is still a notable increase in temperature extending into the free troposphere (Figure 4.8a).

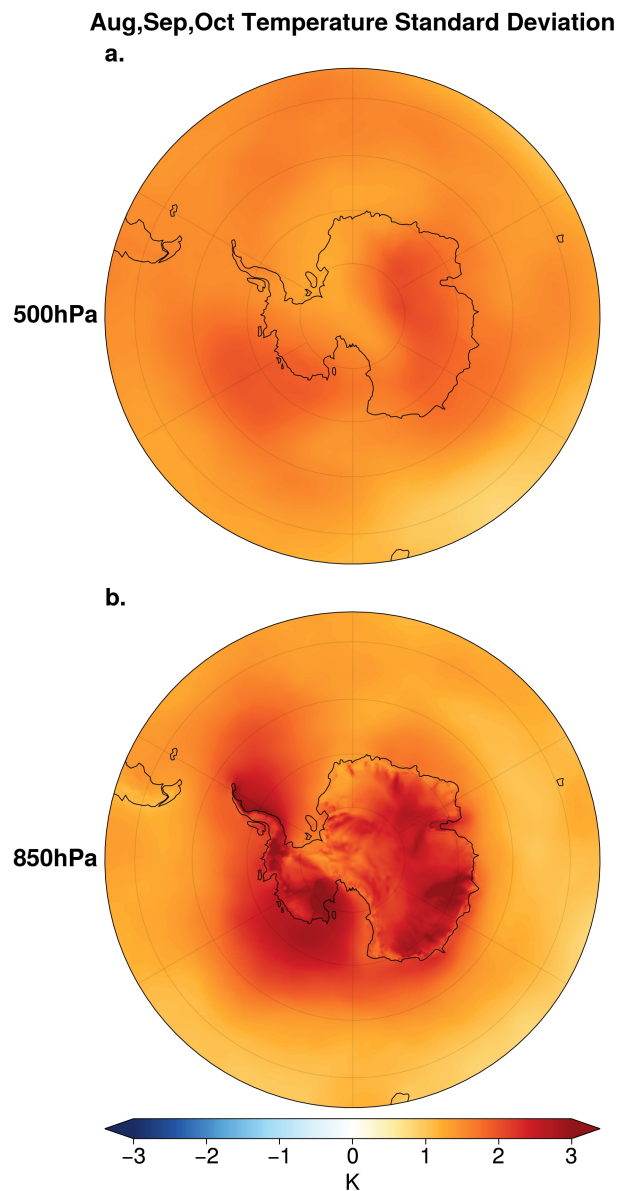


Figure 4.9: Climatological standard deviation of (a) 500 hPa and (b) 850 hPa temperature during the August, September, and October season.

The temperature response at both the 500 hPa and 850 hPa levels is broadly uniform, similar to results from Figure 4.4 and Figure 4.6. However, certain regions exhibit a stronger temperature response, especially at upper levels, than others. Two such regions are near the Ross Sea and in the Western Pacific Ocean sector. Small area averages are taken across those regions for multiple levels, then regressed onto area-averaged SIC loss for the same regions. The vertical profiles of these regressions are shown in Figure 4.8c and d. The strongest temperature response extends from the surface to ~ 700 hPa in both regions, with a steep vertical gradient. Then, from 700 hPa to ~ 400 hPa the regression coefficient is relatively uniform before dropping to zero by 200 hPa.

We can again compare these regression coefficients (calculated per σ SIC) to the standard deviation of temperature (Figure 4.9) to understand the relative impact. Figure 4.9 shows the standard deviation of temperature at 850 hPa and 500 hPa. The standard deviation is generally between 1–3 K and is spatially uniform. Considering that the temperature regression coefficients were between 0.5–1.5 K/ σ , this indicates that a 1σ decrease in sea ice results in upwards of 50% increase in temperature. This is a comparable increase to the increases in THF, precipitation, and cloud fraction predicted by Figure 4.4.

4.3.3 The atmospheric response in sea-ice forced simulations

Until now, the results shown have been from observationally-constrained data. While this data is the closest data we have to true observations, there are uncertainties within the data, and the method of regression analysis we use does not prove causality of the described relationships. We next compare the observational results to two atmosphere-only simulations forced with different states of sea ice to improve confidence in the prior results. The first set of simulations, the transient SIC simulations, were forced with the 1978–2019 time series of SIC from HadISST (see Methods section for more details). The second set of simulations used were run according to the PAMIP protocol (Smith et al. 2019). In the PAMIP-style experiments, we use two specific simulations, one forced with a future state of Antarctic sea ice and one forced with a preindustrial state of Antarctic sea ice. The difference between these two states isolates the impacts of changing Antarctic sea

ice on the atmosphere (see Methods for more details). Both of these simulations allow us to more directly isolate the impacts of sea-ice variability on the atmosphere, because they are only forced by changes in sea ice.

We analyze both of these atmosphere-only experiments because they provide us with different types of results. The transient SIC simulations are useful because we can apply the same gridpoint-by-gridpoint regression analysis to them, which makes comparing results with our observational results clearer. However, the time series of sea ice that the simulations are forced with spans the historical period and is thus not representative of a future climate state. This is where the PAMIP simulations are most useful. The PAMIP simulations allow us to look at changes in the atmosphere under future changes in Antarctic sea ice. Since the PAMIP simulations are not transient simulations, we cannot perform the same regression analysis, making direct comparison with the observational results more challenging. However, the transient SIC simulations use the same model as the PAMIP simulations, so we can compare results between the transient SIC simulations and the PAMIP simulations. In summary, the observational results can be compared to modeled results via the transient simulations, and then we can understand potential implications for the future and non-local relationships using the PAMIP-style simulations.

Starting with the transient SIC simulations, we apply the same gridpoint-by-gridpoint regression analysis as we did for the observational data. The result of this regression analysis is shown in Figure 4.10. Figure 4.10 is comparable to Figure 4.4, and highlights that the same seasonality we saw in the observational results is present in the transient SIC simulation results. The response of THF in these simulations is larger than that in the observations, the precipitation rate response is slightly smaller, and the cloud fraction response is relatively similar (compare Figure 4.10 and Figure 4.4). Based on this, the results from the observations might be slightly underestimating the impact of the sea-ice loss on THF, but slightly overestimating the response of precipitation to sea-ice loss. This regression technique will not perfectly isolate the impacts of sea-ice loss in the observations, so our observational results likely include additional feedbacks or relationships that impact precipitation. It is noteworthy that the transient SIC simulations are atmosphere-only

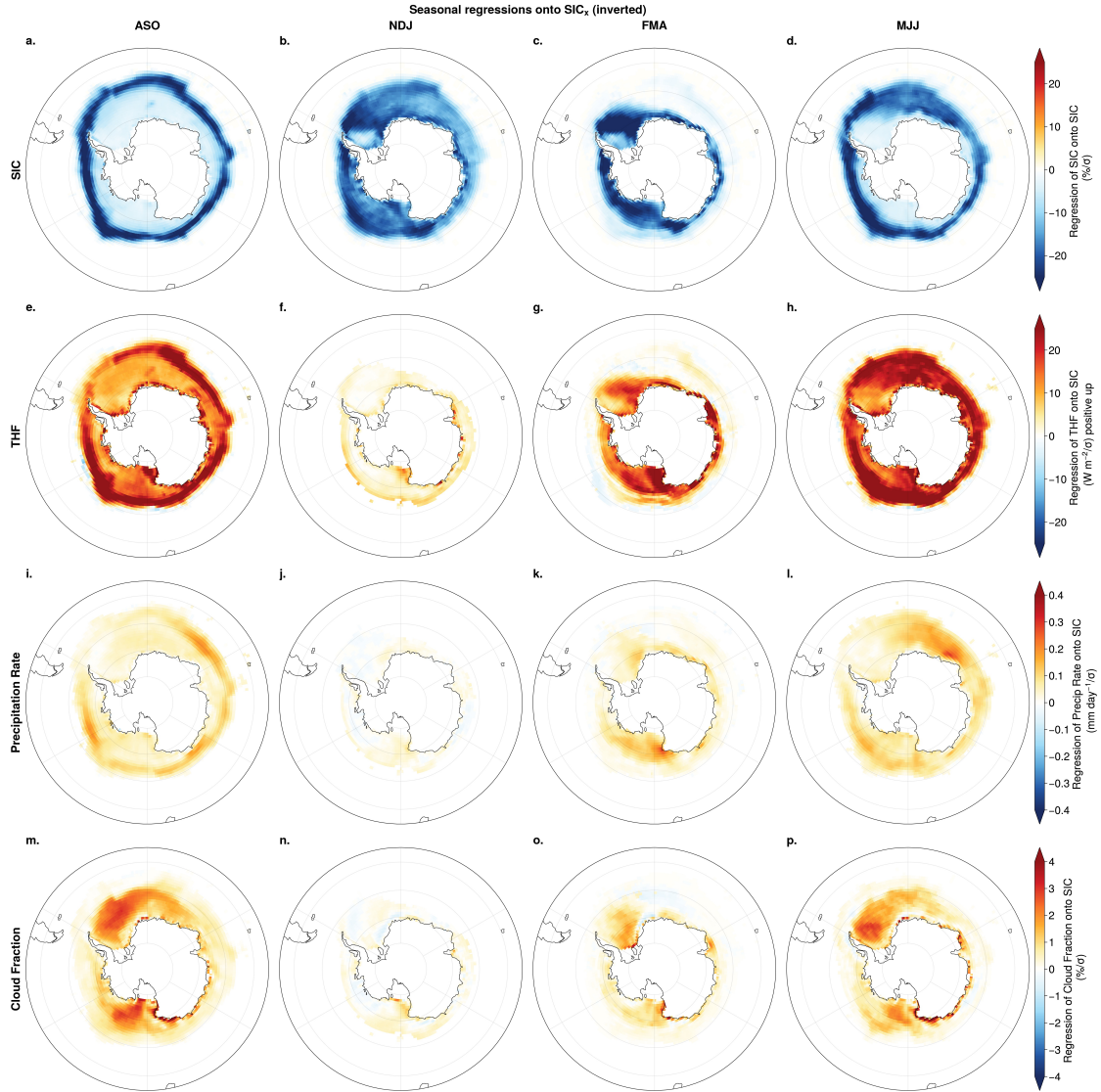


Figure 4.10: As in Figure 4.4 but with transient SIC simulations. Regressions are calculated for each ensemble member, and then an ensemble mean is calculated, which is shown here.

simulations, and previous work has concluded that atmosphere-only simulations underestimate the impacts from Antarctic sea-ice loss (Ayres et al. 2022).

The broad spatial pattern of the results in Figure 4.10 is spatially uniform, but some smaller regions have larger responses. The Bellingshausen-Amundsen Sea sector and the Indian/Pacific Ocean sectors have areas with a local maximum in the response, especially in precipitation, compared to the rest of the regions. In contrast, the Weddell Sea and Ross Sea regions show a larger response in cloud fraction.

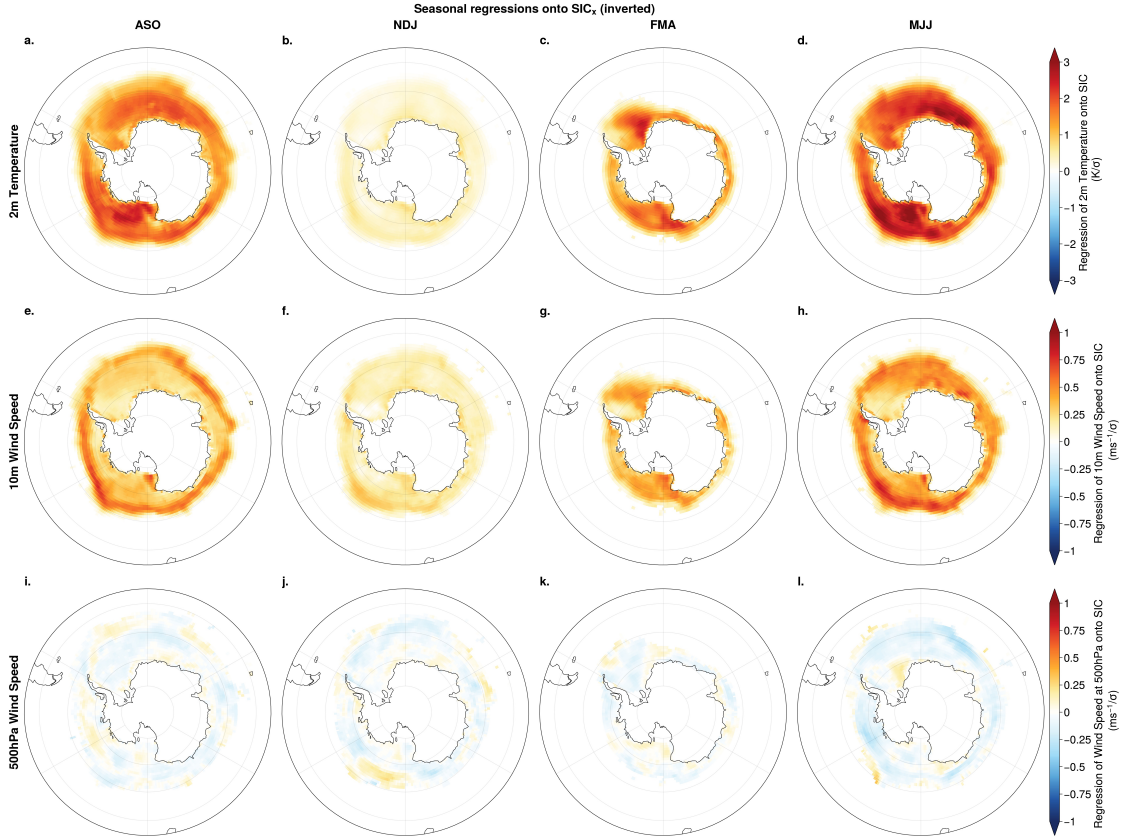


Figure 4.11: As in Figure 4.6 but with the transient SIC simulations. Regressions are calculated for each ensemble member, and then an ensemble mean is calculated, which is shown here.

Next, we look at an analogous figure to Figure 4.6 but with the transient SIC simulations (Figure 4.11). We see broadly similar results as in the observational results. Given sea-ice loss, there is an increase in 2-meter temperature and 10-meter wind speed with little impact on 500 hPa wind speed. The responses of the near-surface wind speed and temperature are spatially uniform, with maxima near the periphery of the sea-ice pack, and a seasonality that is consistent with previous results. The minor impact from sea-ice loss on 500 hPa wind speed is indicative that the local relationships highlighted in Figure 4.11 are important for mixing upper-level winds to the surface, increasing near-surface wind speed, and having downwind impacts on precipitation.

Finally, we look at the potential response of sea-ice loss to upper-level temperatures in the transient SIC simulations in Figure 4.12. Here we see a small but notable response of temperature at 850 hPa due to sea-ice loss, but almost no response at 500 hPa. This is dissimilar to the observa-

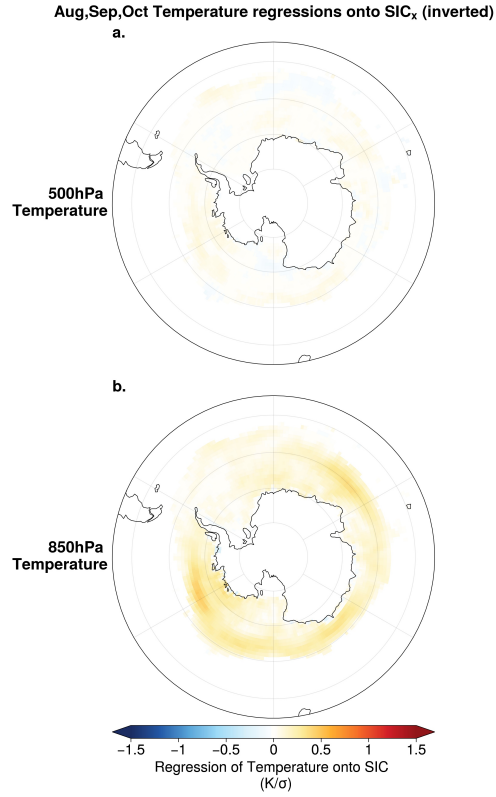


Figure 4.12: Ensemble mean August, September, October season regressions of (a) 500 hPa and (b) 850 hPa temperature onto standardized inverted SIC in the transient SIC simulations. Regressions are calculated for each ensemble member before calculating the ensemble mean.

tional results where there was a notable response at both levels (Figure 4.8a,b). This is noteworthy and indicative that although there are many similarities between the results of the transient SIC simulations and observations, there are also some differences. The transient SIC simulations are not able to capture the vertical depth of the temperature response that was shown in Figure 4.8. This could be due to the lack of coupling with the ocean, which has been shown to limit the predicted vertical extent of Antarctic sea-ice loss responses (Ayres et al. 2022). Something to keep in mind about these simulations is that while they are useful for isolating just the impacts of SIC change, using observations that inherently represent the fully-coupled system may give a more accurate picture of the scale and depth of the responses.

The results from these simulations build confidence that this gridpoint-by-gridpoint regression technique can isolate the impact of sea-ice loss on the local atmosphere. The changes in the atmosphere can be more confidently concluded to be a result of sea-ice loss, not dominated by other factors, since these simulations are only forced with historical SIC. As previously mentioned, these transient SIC simulations isolate the changes in the atmosphere due to sea-ice variability across the historical period. The PAMIP-style experiments allow us to investigate the atmospheric response to future sea-ice change. Additionally, the PAMIP-style experiments cannot be analyzed using the gridpoint-by-gridpoint regression technique by the nature of their structure, so results from them offer insights into the relative roles of the local versus remote relationships between sea ice and the atmosphere.

Figure 4.13 shows the differences in SIC, THF, precipitation rate, and cloud fraction between the PAMIP-style future Antarctic SIC experiment and the preindustrial Antarctic SIC experiment. The difference in SIC (Figure 4.13a-d) is the difference in SIC forcing between the two experiments. Thus, the differences in THF, precipitation rate, and cloud fraction can be thought of as the differences due to the changes in SIC illustrated in Figure 4.13a-d. Starting with the SIC differences, there is a slightly less uniform pattern of SIC loss in the PAMIP simulations compared to the SIC variability plots from the transient SIC and observational results. This is not surprising because these are SIC differences between two climate states versus illustrating the natural SIC

variability. However, it is still clear that the largest SIC differences are along the periphery of the sea-ice pack, and they contract and expand very similarly to the natural variability of SIC demonstrated in Figure 4.4 and Figure 4.10. There is slightly more sea-ice loss in the east Weddell Sea sector and the Bellingshausen-Amundsen Sea sectors, compared with the other regions. This is also highlighted in the response of THF (Figure 4.13e-h).

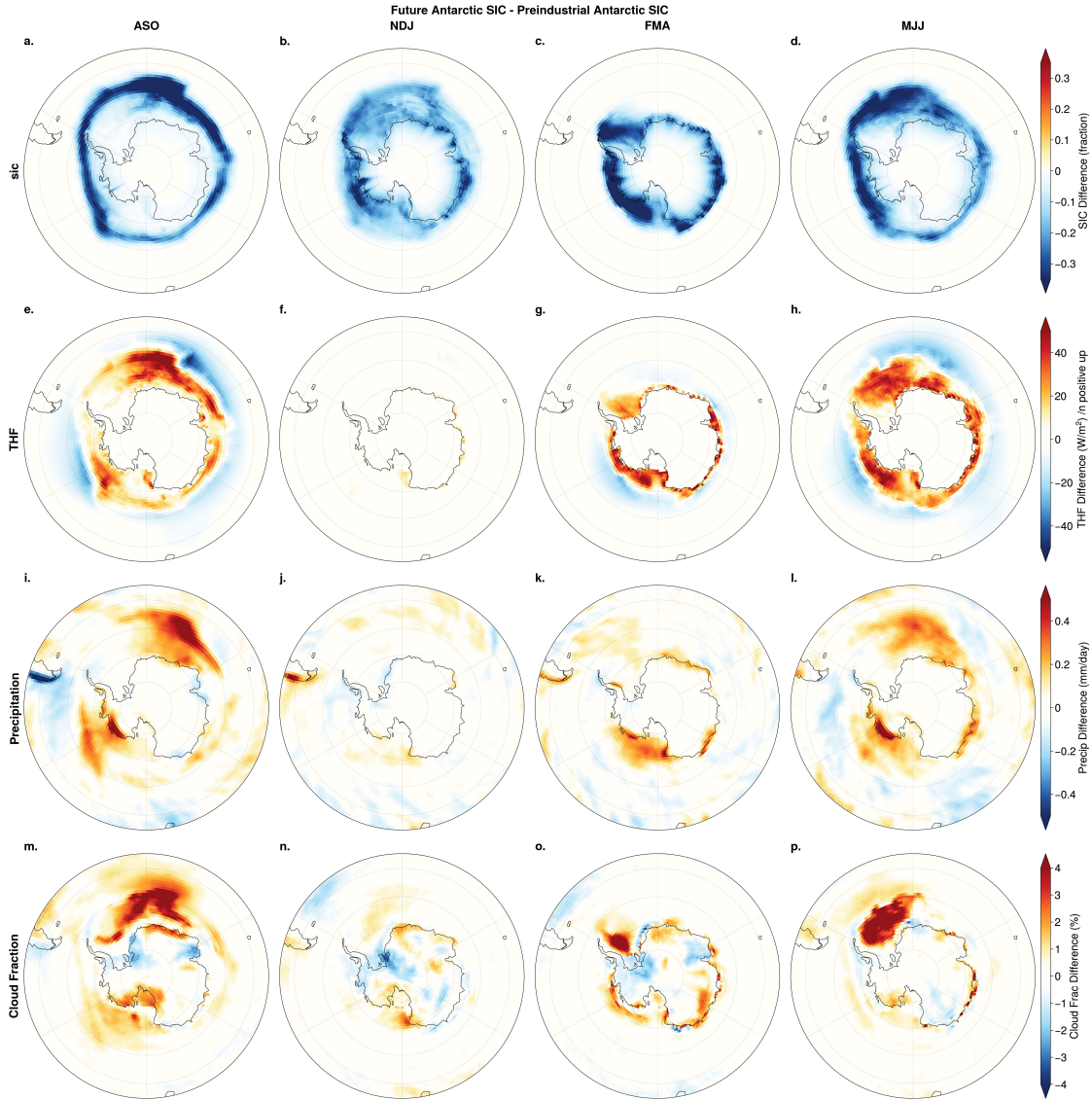


Figure 4.13: The seasonal difference in (a-d) SIC, (e-h) THF, (i-l) precipitation rate, and (m-p) cloud fraction between the future Antarctic SIC simulation and the preindustrial Antarctic SIC simulation from the PAMIP experiments. As in Figure 4.4 each column is a different season.

The difference in THF between the two simulations is clearly positive, with widespread increases in THF everywhere there is sea-ice loss. The regions of largest increases varies by season, with the sea-ice maximum season showing the largest responses in the east Weddell Sea sector and the Bellingshausen-Amundsen Sea sectors (Figure 4.13e) while the sea-ice growth season has more spatially uniform increases (Figure 4.13h). There is almost no change in THF during the sea-ice melting season (Figure 4.13f) and spatially limited changes during the sea-ice minimum season, consistent with the previous results.

Turning attention to the precipitation responses, there is clearly the largest precipitation response during the cold-season months (Figure 4.13i,l). Both the sea-ice maximum and sea-ice growth seasons have the largest change in precipitation in the east Weddell Sea and the Bellingshausen-Amundsen Sea sectors (Figure 4.13i,l), even when the pattern of THF change is more spatially uniform. This indicates that those regions have a stronger relationship with sea-ice loss or are more susceptible to changes in local heating or circulation changes due to sea-ice loss. The cloud fraction changes also have an interesting pattern, but slightly different than the precipitation. The changes in cloud fraction are most pronounced in the Weddell Sea sector (Figure 4.13m,p). There is little response in the Bellingshausen-Amundsen Sea sector, which could be indicative of higher average cloud cover that has lower variability in that region. If that region has consistently very high cloud cover, then sea-ice loss that produced increased cloudiness associated with precipitation would not necessarily impact the total cloud cover very much.

Next, we look at the changes in near-surface temperature/wind speed as well as 500 hPa wind speed in the PAMIP-style experiments (Figure 4.14). The changes in 2-meter temperature and 10-meter wind speed mirror the changes in precipitation and THF. The largest changes occur in the east Weddell Sea and the Bellingshausen-Amundsen Sea sectors during the cold seasons, with a slightly more uniform pattern during the sea-ice growth season (Figure 4.14e,h,i,l). These results are consistent with the transient SIC simulations and observational results: increases in THF promote near-surface warming, which increases local vertical motion, increasing localized precipitation and mixing upper-level winds to the surface. The pattern of 500 hPa winds is different than

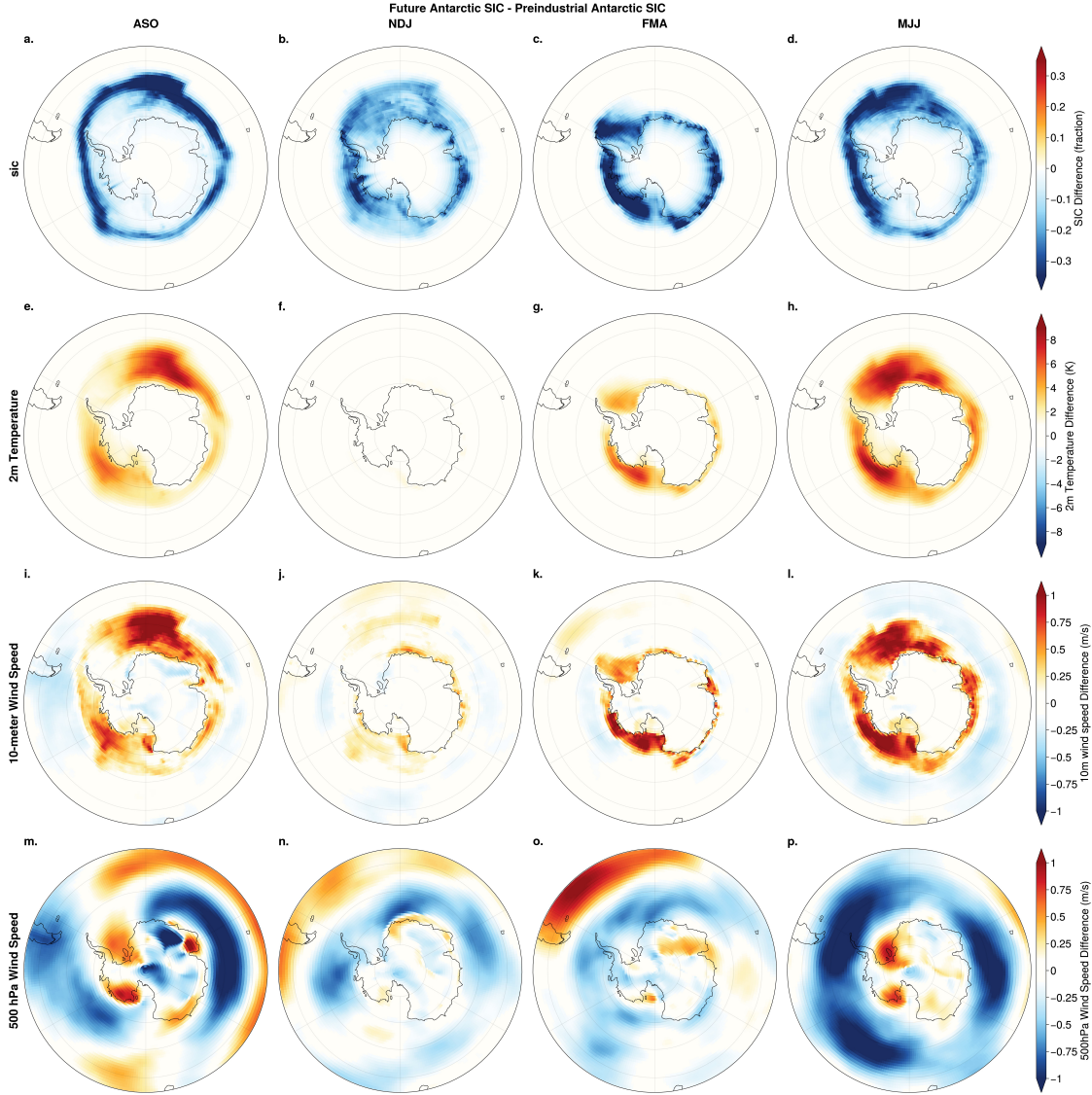


Figure 4.14: Changes in (a-d) SIC, (e-h) 2-meter temperature, (i-l) 10-meter wind speed, and (m-p) 500 hPa wind speed between the future Antarctic SIC experiment and the preindustrial Antarctic SIC experiment from the PAMIP experiments.

the surface response (Figure 4.14m-p). Here we see a spatially uniform weakening of upper-level winds, indicating a shift of the jet, consistent with results from past studies. These results highlight that the impacts of sea-ice loss are not limited to regional impacts via the local relationships, but there is also a component of large-scale circulation changes that can be attributed to sea-ice loss. We see a strengthening of near-surface winds but a weakening of upper-level winds, indicating that

the strengthening of the near-surface winds is not due to a general strengthening of wind speeds at all levels, but rather a mixing down of inherently stronger upper-level wind speeds to lower levels.

Overall, these results using SIC-forced simulations agree well with the correlations predicted by the observation-based results. This highlights the usefulness of the gridpoint-by-gridpoint regression technique for isolating impacts from sea-ice loss in observational data, providing an observational estimate for how changes in sea-ice may impact the regional atmospheric conditions.

4.3.4 Precipitation impacts from future Antarctic sea-ice loss

The PAMIP-style simulations give a sense of the impacts of future Antarctic sea-ice loss. They also provide an opportunity to decompose these future impacts into components due to local and remote relationships with sea-ice loss. To investigate this decomposition, we first take the gridpoint-by-gridpoint regression of precipitation onto sea-ice loss from the transient SIC simulations (Figure 4.10i-l) and multiply it by the sea-ice changes in the PAMIP simulations (Figure 4.13a-d). We recalculate the precipitation-sea ice regressions to be in units of per fraction SIC, not per σ SIC, before we perform this multiplication. That way, when these regression coefficients are multiplied by the change in SIC, the result is a change in precipitation rate of mm day^{-1} . This represents the change in precipitation rate from predicted sea-ice loss due to the local relationships between precipitation and SIC.

Next, we can take the total precipitation response from sea-ice loss predicted by the PAMIP simulations and subtract this portion due to local precipitation-sea ice relationships. The residual from this regression is the portion of precipitation change due to sea-ice loss that is not due to the regional covariability of precipitation and sea ice. The results of this analysis are shown in Figure 4.15. The top row of Figure 4.15 is the total precipitation rate change between the two PAMIP simulations, identical to Figure 4.13i-l. Then the middle row is the fit from multiplying the regression of precipitation onto sea-ice loss in the transient simulations by the sea-ice changes between the two PAMIP simulations, as described above. Finally, the bottom row is the residual.

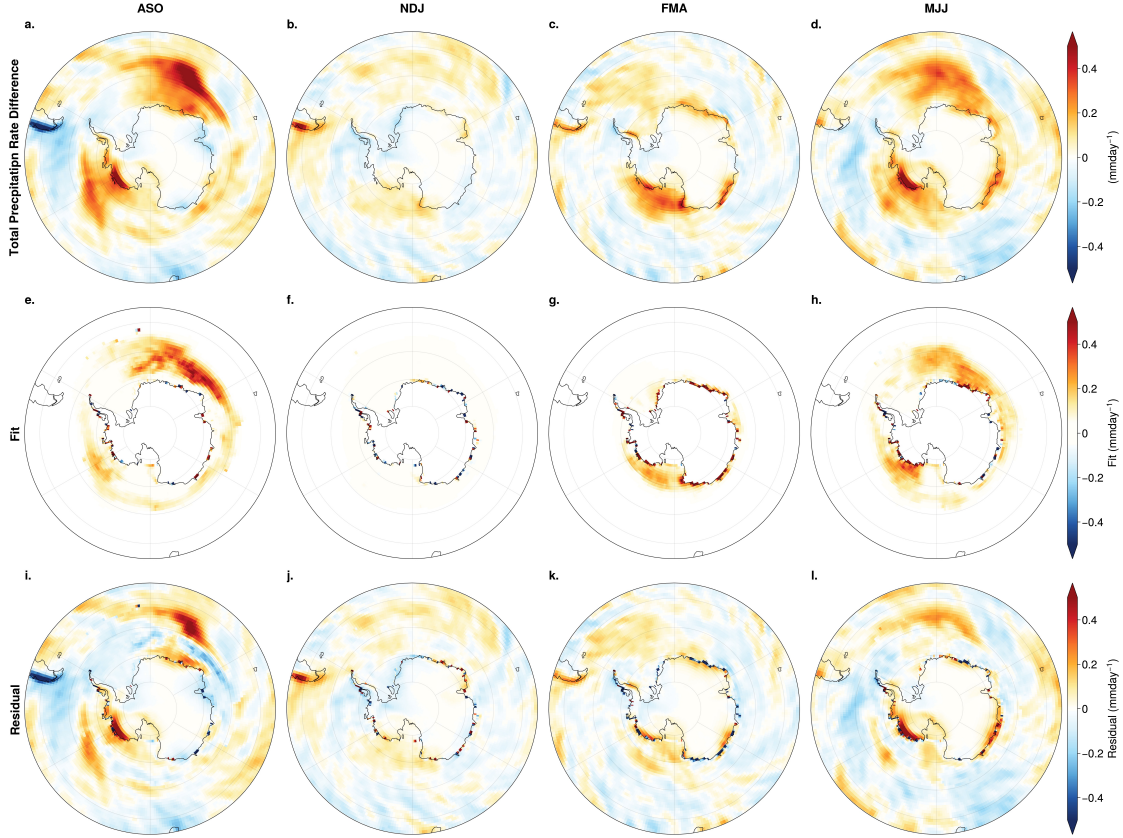


Figure 4.15: Seasonal decomposition of precipitation impacts into local and remote relationships with sea-ice loss. (a-d) Total precipitation difference between the future Antarctic SIC simulation and the preindustrial Antarctic SIC simulation. (e-h) The regression of precipitation onto sea-ice loss from the transient SIC simulations multiplied by sea-ice change between the future Antarctic SIC simulation and the preindustrial Antarctic SIC simulation. (i-l) The residual of the fit calculated by subtracting row two from row one. Each column is the results for each season.

The first thing we see in the Figure 4.15 is that there is a considerable amount of precipitation predicted to occur from future sea-ice loss, just due to the local covariability of SIC and precipitation (Figure 4.15e-h). This is particularly apparent in the cold season, which is expected based on the seasonality established in prior results. Next, comparing the residual in the bottom row with the total precipitation rate change in the top row, we can see that a substantial portion of the precipitation change is due to these local relationships between SIC and precipitation. I.e., there is a notable difference between Figure 4.15a-d and Figure 4.15i-l. However, some precipitation changes cannot be fully explained by the fine grid-scale relationships. These changes are represented by the precipitation response remaining in the residual. This residual may be attributed to a combination

of mechanisms two and three (Section 4.1). Previous works have primarily focused on the large-scale circulation response to sea-ice loss (e.g., England et al. 2018; Ayres et al. 2022), described in mechanism three. However, mechanism two may also explain part of this precipitation response in the residual. Mechanism two describes the relationship between sea-ice loss and increased near-surface wind speeds due to mixing upper-level winds down to the surface. Increased near-surface winds lead to horizontal convergence of the surface flow downwind of the local sea-ice loss, which increases downwind vertical motion and precipitation. Spatially, this alternative mechanism could partially explain the residual precipitation response downwind (east) in the locations of horizontal convergence (Figure 4.15i-l).

4.3.5 Local relationships in a high-resolution climate model

The final part of these results briefly explores what these local relationships look like in a fully coupled model, specifically the high-resolution fully-coupled model CESM-HR (described in section 4.3.2). Even though we have looked at the local relationships in models, via the transient SIC simulations and the PAMIP-style simulations, those experiments were atmosphere-only, not coupled to the ocean. Additionally, in those modeling experiments and in the observational data we use, sea-ice thickness is set to a fixed value; it doesn't vary even as sea ice melts or grows (Smith et al. 2019; Hersbach et al. 2020). Thus, there is a chance that THF, in particular, could be misrepresented in this data. The CESM-HR model has variable sea-ice thickness and has been shown to represent Antarctic sea-ice well (Chang et al. 2020).

Figure 4.16 shows results of the gridpoint-by-gridpoint regression of SIC, THF, precipitation rate, and cloud fraction onto standardized inverted SIC, from the CESM-HR historical simulation. We see broadly similar results as in Figure 4.4 and Figure 4.10, with a strong seasonality and increases in THF, precipitation rate, and cloud fraction correlated with sea-ice loss. The pattern of sea-ice variability is slightly different in these simulations, resulting in a slightly different pattern of the atmospheric response. Part of this differing pattern of sea-ice variability can be attributed to the misrepresentation of a polynya in the Weddell gyre (Section 2.2; Chang et al. 2020). Despite this,

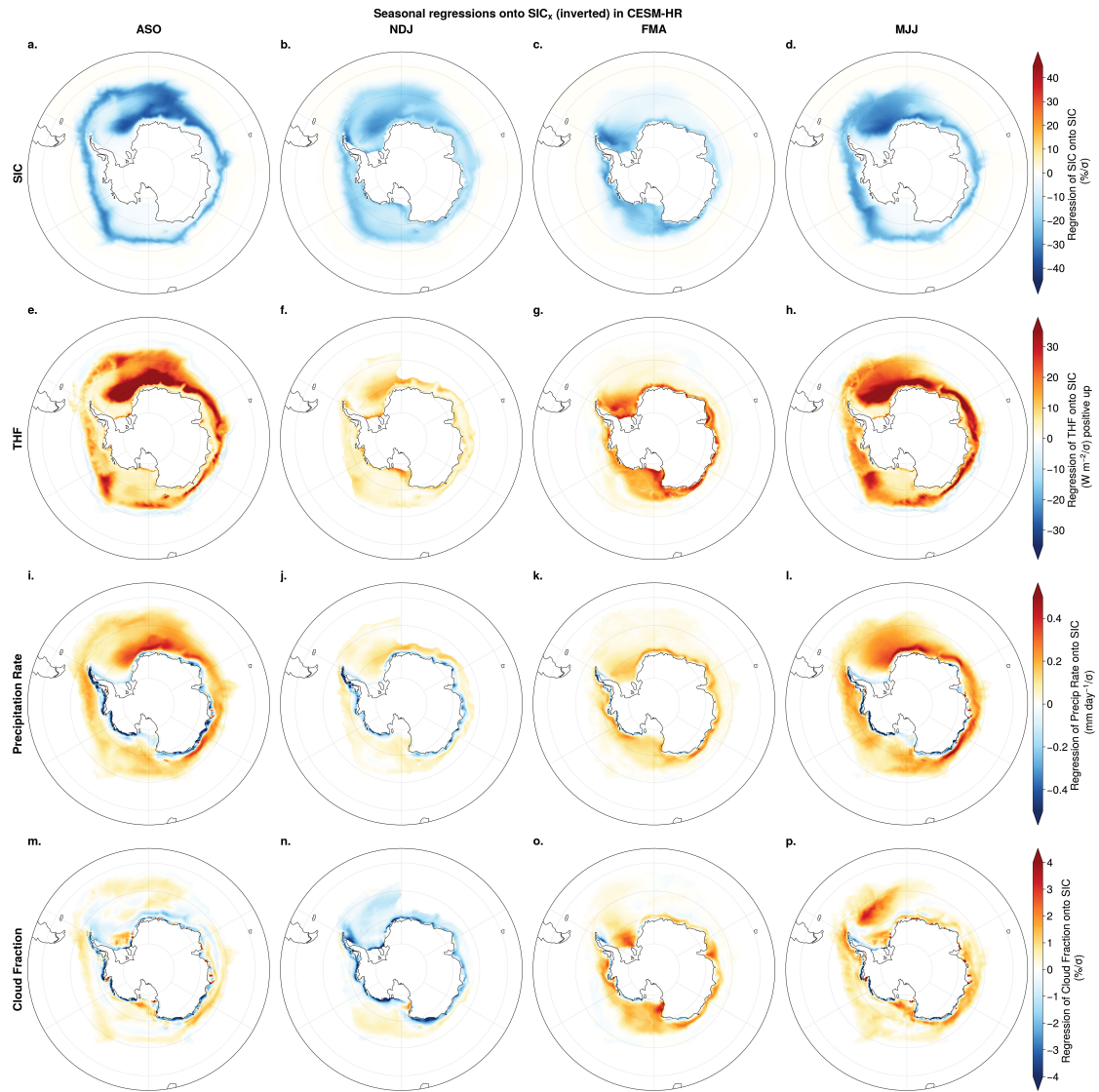


Figure 4.16: As in Figure 4.4 but with CESM-HR historical simulation. These are ensemble mean results. Regressions are calculated for each ensemble member and then the ensemble mean is calculated.

the way that the pattern of the atmospheric response maps onto the pattern of SIC variability is very similar to the observational and transient SIC simulation results. The agreement the Figure 4.16 results with the previous results indicates that the inclusion of a variable sea-ice thickness does not change our conclusions. Additionally, since this is a fully-coupled model, it is encouraging to see similar results to the transient SIC simulation results, which isolate just the impacts of sea-ice loss (Figure 4.10).

4.4 Discussion

Antarctic sea ice has experienced multiple record negative anomalies over the past decade. While there has been considerable effort towards determining the causes behind these anomalies, there have only been a few recent studies focused on the potential impacts (e.g., England et al. 2018; England et al. 2020a,b; Ayres et al. 2022; Hay and Kushner 2024; Josey et al. 2024; Zhang et al. 2024). Within that body of work, even fewer have been observation-based studies (Josey et al. 2024; Zhang et al. 2024). This work aims to add to this body of work by providing an observational estimate of the impacts of Antarctic sea-ice loss across the observational record, and comparing these results to both atmosphere-only and fully-coupled modeling experiments.

We show that by using a gridpoint-by-gridpoint regression technique, the local impacts of Antarctic sea-ice loss on the atmosphere can be effectively isolated in observational data. Results show that given a decrease in sea ice, there is a strong correlation with increased THF, precipitation rate, cloud fraction, temperature, and near-surface winds (Figure 4.4, Figure 4.6, Figure 4.8). Quantitatively, given a one standard deviation decrease in sea ice, the results predict an increase in THF and precipitation rate of 50–60% and an increase in cloud fraction of 40%. Additionally, one standard deviation of sea-ice loss is predicted to result in upwards of a 50% increase in temperature from the surface into the free troposphere.

These results are then compared to atmosphere-only sea-ice forced simulations, one with transient SIC forcing, and one with SIC forcing from future and preindustrial states. The results from the transient SIC simulations are similar to the observational results, with widespread positive

correlation of atmospheric variables with sea-ice loss using the same gridpoint-by-gridpoint regression technique (Figure 4.10). The PAMIP-style experiments highlight that these relationships are expected to affect the local atmosphere in the future, under future sea-ice loss (Figure 4.13).

Combining the PAMIP-style experiments and the gridpoint-by-gridpoint regression analysis allows us to decompose the portion of the predicted precipitation changes due to the local covariability versus the more remote relationships (Figure 4.15). As discussed in Section 4.1, there are three main ways that sea-ice loss can impact the local precipitation. Sea-ice loss can 1) increase THF and vertical motion, leading to increased precipitation via local covariability, 2) mix free tropospheric winds to the surface, increases near-surface wind speeds which results in horizontal convergence and enhanced precipitation downwind of the sea-ice loss regions, and 3) cause changes in baroclinicity through changes in the temperature gradient, resulting in an equatorward shift of the stormtracks. This work shows that the first mechanism, local covariability the atmosphere and sea ice, is critical for understanding the impacts of sea-ice loss. Additionally, these results highlight the importance of the second mechanism, previously overlooked in prior work. The results show an increase in near-surface winds/temperature but not an enhancement of upper-level winds, within the gridpoint-by-gridpoint regression results (Figure 4.6, Figure 4.11). This provides evidence that sea-ice loss is mixing upper-level winds to the surface, highlighting mechanism two. There is then evidence of increased precipitation downstream of the sea-ice anomalies (Figure 4.15), indicative of downwind horizontal convergence of the surface flow.

This study provides the groundwork for future studies to utilize observationally-constrained data when investigating Antarctic sea-ice loss. While models are useful, especially the sea-ice forced simulations shown here, it is important to gain more insights into how recent recorded Antarctic sea-ice anomalies have impacted the climate system, using observationally-constrained data. Observational studies like this will hopefully continue to help the improvement of models in the future, continuing to reduce biases and improve the representation of the climate system.

Chapter 5

Conclusions and Future Work

Antarctic sea ice has experienced a very interesting evolution across the observational period, with a slight positive trend until 2015 and then rapid decline from 2015 to the present day. There has been prior research both focused on the driving mechanisms of Antarctic sea-ice variability (e.g., Stammerjohn et al. 2008; Simpkins et al. 2012; Hobbs et al. 2016; Meehl et al. 2016; Purich et al. 2018; Doddridge and Marshall 2017; Turner et al. 2017; Schlosser et al. 2018; Meehl et al. 2019; Blanchard Wrigglesworth et al. 2021; Dong et al. 2022; Purich and Doddridge 2023; Jena et al. 2024; see Chapter 1 for additional references), as well as impacts of this sea-ice variability on the climate system (e.g., Bader et al. 2013; England et al. 2018; Rea et al. 2024; England et al. 2020a,b; Ayres et al. 2022; Josey et al. 2024; Zhang et al. 2024; see Chapter 1 for additional references). This dissertation focused on the drastic changes in Antarctic sea ice in the last decade and aimed to provide new insights into both the driving mechanisms and potential implications of such changes. Specifically, this dissertation focused on the two-way interactions between the atmosphere and sea ice: how changes in the atmospheric circulation can impact sea-ice variability and how sea-ice variability can impact local atmospheric conditions. We primarily focused on using observationally-constrained data, partially because there is a smaller number of previous observational studies in this area. Results from model output were used to accompany these results, both to compare representations of important relationships seen in observational data, but also to provide additional insights from particular experiments.

In Chapter 3, we provided novel observational insights into the influence of the SAM on recent hemispheric-mean Antarctic sea-ice variability. The results shown in this chapter highlighted a key but overlooked seasonality in the relationship between the SAM and SIA. During the sea-ice maximum, positive anomalies in the SAM are linked to *decreases* in SIA. During the sea-ice minimum, positive anomalies in the SAM are linked to *increases* in SIA. Following positive anomalies in the SAM during the sea ice minimum, sea-ice anomalies persist for up to ~ 4 months,

while during the sea ice maximum, sea-ice anomalies persist for up to a full year. This indicates that positive anomalies in the SAM during the sea ice maximum are capable of impacting sea ice for the entire following year, and thus have an outsized impact on annual-mean SIA. Over 30% of the variance in annual-mean SIA can be explained by the SAM during the sea-ice maximum. Variations in the SAM during other months of the year only explain a small fraction of year-to-year SIA variance.

This large persistence in SIA anomalies was attributed to feedbacks with SW clear-sky fluxes and changes in ocean heat content. Specifically, negative SIA anomalies during the sea-ice maximum season resulted in increased SW flux into the newly open ocean surface, increasing near-surface ocean temperatures and providing conditions for negative SIA anomalies to persist. This strong relationship between the SAM and SIA during the sea-ice maximum can explain some of the recent changes in SIA. The SAM has exhibited particularly large variations in the last decade that are consistent with the large variations in SIA. This work presented a previously overlooked seasonality of the relationship between SIA and the SAM, and highlighted how this seasonality is key to understanding the full impact SAM variability could have on Antarctic sea ice.

In Chapter 4, we provided observational insights into the impact of Antarctic sea-ice loss on the local atmospheric circulation using a novel gridpoint-by-gridpoint regression analysis. As noted in the chapter, prior work has focused on model output, with only a few studies using observational data. Our work aimed to add to this body of literature by analyzing the relationships between sea-ice loss and atmospheric conditions, such as turbulent heat flux, precipitation, cloud fraction, temperature, and winds within observational data. The results highlighted a strong relationship between decreases in sea ice and increases in the previously mentioned atmospheric variables. These relationships have a strong seasonality, strongest during the winter/spring seasons. Quantitatively, given one standard deviation of sea-ice loss, we find that these results predict a 50–60% increase in THF and precipitation rate, a 40% increase in cloud fraction, and upwards of a 50% increase in near-surface temperature. This is consistent with prior model-based studies, and showed that this regression technique effectively isolates the impacts of sea-ice loss within observational data.

A key part of the analyses in Chapter 4 was the comparison of the observational results with model output, both from a fully-coupled model and from atmosphere-only simulations. By utilizing the same gridpoint-by-gridpoint regression technique in the atmosphere-only simulation forced with transient sea ice, we confirmed that the observational regression results are most likely due to sea-ice loss, not other confounding factors. These atmosphere-only simulations also provided the opportunity to investigate the pathways by which sea-ice loss can impact local precipitation. Results indicated that sea-ice loss increases local THF, increasing vertical velocity, and thus precipitation. By decomposing the PAMIP-style experiments into the portion from the local relationships and a residual, we showed that the local relationships explain a large portion of future precipitation change, but they are not the only factor. Large-scale changes in the circulation due to changes in baroclinicity from sea-ice loss can impact patterns of precipitation. Alternatively, sea-ice loss can result in increased surface wind, from the mixing of free tropospheric winds to the surface, leading to an increase in precipitation downwind of where the sea-ice loss occurred. This work highlighted this final mechanism, which has been overlooked in previous work, is an active pathway by which sea-ice loss impacts precipitation. Results from this chapter provided evidence that we can see impacts from Antarctic sea-ice loss within observational data, and highlighted that, given model biases, using this observationally-constrained data is important for providing an estimate of potential impacts we could see in the future.

5.1 Future Work

This dissertation addresses the two-way interactions between Antarctic sea ice and the atmosphere, investigating both the mechanisms of and impacts from Antarctic sea-ice loss. The results from this work provide a jumping-off point for many different avenues of future research on this topic by sparking additional questions about the topic. Such additional questions include:

- How has the sea ice thickness changed across the record, and would thinner sea ice make the ice pack more variable?

- Why is the SAM experiencing more variability later in the record? What could be changing the SAM?
- What are the specific mechanisms by which the SAM impacts sea ice, and what are their relative importance?
- What is the large-scale atmospheric response to sea-ice loss, how can we quantify this in observational data?
- Is there a two-way feedback between the SAM and sea ice? Can sea ice loss driven by a positive SAM result in changes in the SAM?
- What is the importance of feedbacks between the ice and atmosphere that could drive the recent changes in the Antarctic climate system?
- How can sea ice loss impact land ice?

Based off of these questions as well as open areas of research in the field, a couple of future research directions are:

1. Utilizing this gridpoint-by-gridpoint regression analysis to conduct a comprehensive evaluation of the relationship between Antarctic sea ice and the atmosphere within CMIP6 models. Past work, including this one, has only looked at relationships within one or two models. There is a need to understand what these relationships look like in many different models to understand what the potential bounds of the relationships are. This regression technique can be applied to any fully-coupled CMIP6 model for any simulation, providing a unique opportunity for an inter-model comparison with fully-coupled models of these relationships.
2. The results from Chapter 3 highlight that the SAM has more impact on SIA than previously thought. The important seasonality of this relationship was only briefly investigated in a climate model; thus, a natural next step of this work would be to complete a similar analysis using many different climate models. This would provide the opportunity to get a better

sense of what the SIA-SAM relationship looks like in models and whether a misrepresentation of this relationship is contributing to model biases. Specifically, the inability of models to simulate the observed Antarctic sea-ice trends.

3. Conducting similar analysis techniques as in Chapter 3, but for different modes of climate variability. We briefly investigated the relationship between ENSO and SIA in Chapter 3, but a more comprehensive analysis of what modes of atmospheric variability explain the most variability in hemispheric-mean Antarctic sea ice has not been done. Many previous studies that have looked at alternative modes of variability, looked at modeled data or focused on particular regions or seasons. Since we found such a strong seasonality to the relationship between the SAM and SIA, it would be worthwhile to see if there are important seasonal relationships that have been overlooked with other modes of variability.
4. Utilizing the gridpoint-by-gridpoint regression technique to understand how the resolution of models impacts our understanding of the relationship between sea-ice loss and the atmosphere. With more models having higher resolution, or the ability for variable resolution, it is important to understand if our understanding of the impacts of Antarctic sea-ice loss are impacted by the available resolution of models.
5. Understanding the relative physical processes to variations in the SAM during the sea-ice maximum that contributed to the large variability in the SAM during the last decade. We highlighted the importance of the particularly large variations in the SAM for impacting sea-ice anomalies; however, it was outside the scope of this work to focus on why the SAM experienced these variations. Using nudged model simulations, it is possible to isolate the impacts from various factors, such as SSTs or wind patterns from other regions. This could provide some understanding of what caused the large variations in the SAM and further build a physical understanding of the important processes for Antarctic sea-ice variability.

These are just a few different future avenues of research, but Antarctic sea-ice variability is an active area of research due to its important role in the Earth's system. It will be critical to

continue to better understand the interactions Antarctic sea ice has with the rest of the climate system, especially as the climate system continues to change in the future.

Bibliography

- Alexander, M. A., Deser, C., & Timlin, M. S. (1999). The Reemergence of SST Anomalies in the North Pacific Ocean. <https://journals.ametsoc.org/view/journals/clim/12/8/1520-0442\1999\012\2419\trosai\2.0.co\2.xml>
- Arblaster, J. M., & Meehl, G. A. (2006). Contributions of External Forcings to Southern Annular Mode Trends. *Journal of Climate*, 19(12), 2896–2905. <https://doi.org/10.1175/JCLI3774.1>
- Ayres, H. C., Screen, J. A., Blockley, E. W., & Bracegirdle, T. J. (2022). The Coupled Atmosphere–Ocean Response to Antarctic Sea Ice Loss. <https://doi.org/10.1175/JCLI-D-21-0918.1>
- Bader, J., Flügge, M., Kvamstø, N. G., Mesquita, M. D. S., & Voigt, A. (2013). Atmospheric winter response to a projected future Antarctic sea-ice reduction: A dynamical analysis. *Climate Dynamics*, 40(11), 2707–2718. <https://doi.org/10.1007/s00382-012-1507-9>
- Baker, H. S., Woollings, T., & Mbengue, C. (2017). Eddy-Driven Jet Sensitivity to Diabatic Heating in an Idealized GCM. <https://doi.org/10.1175/JCLI-D-16-0864.1>
- Batrak, Y., & Müller, M. (2019). On the warm bias in atmospheric reanalyses induced by the missing snow over Arctic sea-ice. *Nature Communications*, 10(1), 4170. <https://doi.org/10.1038/s41467-019-11975-3>
- Bell, B., Hersbach, H., Simmons, A., Berrisford, P., Dahlgren, P., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Radu, R., Schepers, D., Soci, C., Villaume, S., Bidlot, J.-R., Haimberger, L., Woollen, J., Buontempo, C., & Thépaut, J.-N. (2021). The ERA5 global reanalysis: Preliminary extension to 1950. *Quarterly Journal of the Royal Meteorological Society*, 147(741), 4186–4227. <https://doi.org/10.1002/qj.4174>
- Bitz, C. M., & Polvani, L. M. (2012). Antarctic climate response to stratospheric ozone depletion in a fine resolution ocean climate model. *Geophysical Research Letters*, 39(20). <https://doi.org/10.1029/2012GL053393>
- Blackport, R., & Kushner, P. J. (2016). The Transient and Equilibrium Climate Response to Rapid Summertime Sea Ice Loss in CCSM4. <https://doi.org/10.1175/JCLI-D-15-0284.1>
- Blackport, R., & Kushner, P. J. (2017). Isolating the Atmospheric Circulation Response to Arctic Sea Ice Loss in the Coupled Climate System. <https://doi.org/10.1175/JCLI-D-16-0257.1>
- Blanchard-Wrigglesworth, E., Armour, K. C., Bitz, C. M., & DeWeaver, E. (2011). Persistence and Inherent Predictability of Arctic Sea Ice in a GCM Ensemble and Observations. <https://doi.org/10.1175/2010JCLI3775.1>

- Blanchard-Wrigglesworth, E., Roach, L. A., Donohoe, A., & Ding, Q. (2021). Impact of Winds and Southern Ocean SSTs on Antarctic Sea Ice Trends and Variability. <https://doi.org/10.1175/JCLI-D-20-0386.1>
- Blanchard-Wrigglesworth, E., Eisenman, I., Zhang, S., Sun, S., & Donohoe, A. (2022). New perspectives on the enigma of expanding Antarctic sea ice, *Eos*, 103, <https://doi.org/10.1029/2022EO220076>.
- Bocquet, M., Fleury, S., Rémy, F., & Piras, F. (2024). Arctic and Antarctic Sea Ice Thickness and Volume Changes From Observations Between 1994 and 2023. *Journal of Geophysical Research: Oceans*, 129(11), e2023JC020848. <https://doi.org/10.1029/2023JC020848>
- Bonan, D. B., Dörr, J., Wills, R. C. J., Thompson, A. F., & Årthun, M. (2024). Sources of low-frequency variability in observed Antarctic sea ice. *The Cryosphere*, 18(4), 2141–2159. <https://doi.org/10.5194/tc-18-2141-2024>
- Bretherton, C. S., Widmann, M., Dymnikov, V. P., Wallace, J. M., & Bladé, I. (1999). The Effective Number of Spatial Degrees of Freedom of a Time-Varying Field. https://journals.ametsoc.org/view/journals/clim/12/7/1520-0442/_1999_012_1990_tenosd_2.0.co_2.xml
- Butler, A. H., Thompson, D. W. J., & Heikes, R. (2010). The Steady-State Atmospheric Circulation Response to Climate Change–like Thermal Forcings in a Simple General Circulation Model. <https://doi.org/10.1175/2010JCLI3228.1>
- Cavalieri, D. J., Gloersen, P., & Campbell, W. J. (1984). Determination of sea ice parameters with the NIMBUS 7 SMMR. *Journal of Geophysical Research: Atmospheres*, 89(D4), 5355–5369. <https://doi.org/10.1029/JD089iD04p05355>
- Chang, P., Zhang, S., Danabasoglu, G., Yeager, S. G., Fu, H., Wang, H., Castruccio, F. S., Chen, Y., Edwards, J., Fu, D., Jia, Y., Laurindo, L. C., Liu, X., Rosenbloom, N., Small, R. J., Xu, G., Zeng, Y., Zhang, Q., Bacmeister, J., ... Wu, L. (2020). An Unprecedented Set of High-Resolution Earth System Simulations for Understanding Multiscale Interactions in Climate Variability and Change. *Journal of Advances in Modeling Earth Systems*, 12(12), e2020MS002298. <https://doi.org/10.1029/2020MS002298>
- Chelton, D. B., Schlax, M. G., Freilich, M. H., & Milliff, R. F. (2004). Satellite Measurements Reveal Persistent Small-Scale Features in Ocean Winds. *Science*, 303(5660), 978–983. <https://doi.org/10.1126/science.1091901>
- Chung, E.-S., Kim, S.-J., Timmermann, A., Ha, K.-J., Lee, S.-K., Stuecker, M. F., Rodgers, K. B., Lee, S.-S., & Huang, L. (2022). Antarctic sea-ice expansion and Southern Ocean cooling linked

- to tropical variability. *Nature Climate Change*, 12(5), 461–468. <https://doi.org/10.1038/s41558-022-01339-z>
- Ciasto, L. M., Simpkins, G. R., & England, M. H. (2015). Teleconnections between Tropical Pacific SST Anomalies and Extratropical Southern Hemisphere Climate. *Journal of Climate*, 28(1), 56–65. <https://doi.org/10.1175/JCLI-D-14-00438.1>
- Ciasto, L. M., & Thompson, D. W. J. (2008). Observations of Large-Scale Ocean–Atmosphere Interaction in the Southern Hemisphere. <https://doi.org/10.1175/2007JCLI1809.1>
- Comiso, J. C., Cavalieri, D. J., Parkinson, C. L., & Gloersen, P. (1997). Passive microwave algorithms for sea ice concentration: A comparison of two techniques. *Remote Sensing of Environment*, 60(3), 357–384. [https://doi.org/10.1016/S0034-4257\(96\)00220-9](https://doi.org/10.1016/S0034-4257(96)00220-9)
- Comiso, J. C., & Nishio, F. (2008). Trends in the sea ice cover using enhanced and compatible AMSR-E, SSM/I, and SMMR data. *Journal of Geophysical Research: Oceans*, 113(C2). <https://doi.org/10.1029/2007JC004257>
- Danabasoglu, G., Lamarque, J.-F., Bacmeister, J., Bailey, D. A., DuVivier, A. K., Edwards, J., Emmons, L. K., Fasullo, J., Garcia, R., Gettelman, A., Hannay, C., Holland, M. M., Large, W. G., Lauritzen, P. H., Lawrence, D. M., Lenaerts, J. T. M., Lindsay, K., Lipscomb, W. H., Mills, M. J., ... Strand, W. G. (2020). The Community Earth System Model Version 2 (CESM2). *Journal of Advances in Modeling Earth Systems*, 12(2), e2019MS001916. <https://doi.org/10.1029/2019MS001916>
- Deser, C., Sun, L., Tomas, R. A., & Screen, J. (2016). Does ocean coupling matter for the northern extratropical response to projected Arctic sea ice loss? *Geophysical Research Letters*, 43(5), 2149–2157. <https://doi.org/10.1002/2016GL067792>
- Deser, C., Tomas, R. A., & Sun, L. (2015). The Role of Ocean–Atmosphere Coupling in the Zonal-Mean Atmospheric Response to Arctic Sea Ice Loss. <https://doi.org/10.1175/JCLI-D-14-00325.1>
- Deser, C., Tomas, R., Alexander, M., & Lawrence, D. (2010). The Seasonal Atmospheric Response to Projected Arctic Sea Ice Loss in the Late Twenty-First Century. <https://doi.org/10.1175/2009JCLI3053.1>
- Deser, C., Walsh, J. E., & Timlin, M. S. (2000). Arctic Sea Ice Variability in the Context of Recent Atmospheric Circulation Trends. https://journals.ametsoc.org/view/journals/clim/13/3/1520-0442_2000_013_0617_asivit_2.0.co_2.xml

- Doddridge, E. W., & Marshall, J. (2017). Modulation of the Seasonal Cycle of Antarctic Sea Ice Extent Related to the Southern Annular Mode. *Geophysical Research Letters*, 44(19), 9761–9768. <https://doi.org/10.1002/2017GL074319>
- Dong, Y., Pauling, A. G., Sadai, S., & Armour, K. C. (2022). Antarctic Ice-Sheet Meltwater Reduces Transient Warming and Climate Sensitivity Through the Sea-Surface Temperature Pattern Effect. *Geophysical Research Letters*, 49(24), e2022GL101249. <https://doi.org/10.1029/2022GL101249>
- Dong, Y., Polvani, L. M., & Bonan, D. B. (2023). Recent Multi-Decadal Southern Ocean Surface Cooling Unlikely Caused by Southern Annular Mode Trends. *Geophysical Research Letters*, 50(23), e2023GL106142. <https://doi.org/10.1029/2023GL106142>
- DuVivier, A. K., Vavrus, S. J., Holland, M. M., Landrum, L., Shields, C. A., & Thaker, R. (2023). Investigating Future Arctic Sea Ice Loss and Near-Surface Wind Speed Changes Related to Surface Roughness Using the Community Earth System Model. *Journal of Geophysical Research: Atmospheres*, 128(20), e2023JD038824. <https://doi.org/10.1029/2023JD038824>
- England, M., Polvani, L., & Sun, L. (2018). Contrasting the Antarctic and Arctic Atmospheric Responses to Projected Sea Ice Loss in the Late Twenty-First Century. <https://doi.org/10.1175/JCLI-D-17-0666.1>
- England, M. R., Polvani, L. M., & Sun, L. (2020a). Robust Arctic warming caused by projected Antarctic sea ice loss. *Environmental Research Letters*, 15(10), 104005. <https://doi.org/10.1088/1748-9326/abaada>
- England, M. R., Polvani, L. M., Sun, L., & Deser, C. (2020b). Tropical climate responses to projected Arctic and Antarctic sea-ice loss. *Nature Geoscience*, 13(4), 275–281. <https://doi.org/10.1038/s41561-020-0546-9>
- Espinosa, Z. I., Blanchard-Wrigglesworth, E., & Bitz, C. M. (2024). Understanding the drivers and predictability of record low Antarctic sea ice in austral winter 2023. *Communications Earth & Environment*, 5(1), 1–9. <https://doi.org/10.1038/s43247-024-01772-2>
- Ferreira, D., Marshall, J., Bitz, C. M., Solomon, S., & Plumb, A. (2015). Antarctic Ocean and Sea Ice Response to Ozone Depletion: A Two-Time-Scale Problem. <https://doi.org/10.1175/JCLI-D-14-00313.1>
- Fogt, R. L., & Marshall, G. J. (2020). The Southern Annular Mode: Variability, trends, and climate impacts across the Southern Hemisphere. *WIREs Climate Change*, 11(4), e652. <https://doi.org/10.1002/wcc.652>

- Fretwell, P. T., Boutet, A., & Ratcliffe, N. (2023). Record low 2022 Antarctic sea ice led to catastrophic breeding failure of emperor penguins. *Communications Earth & Environment*, 4(1), 273. <https://doi.org/10.1038/s43247-023-00927-x>
- Fyfe, J. C., Gillett, N. P., & Marshall, G. J. (2012). Human influence on extratropical Southern Hemisphere summer precipitation. *Geophysical Research Letters*, 39(23). <https://doi.org/10.1029/2012GL054199>
- Garza-Girón, R., & Tulaczyk, S. M. (2024). Brief communication: Significant biases in ERA5 output for the McMurdo Dry Valleys region, Antarctica. *The Cryosphere*, 18(3), 1207–1213. <https://doi.org/10.5194/tc-18-1207-2024>
- Hall, A., & Visbeck, M. (2002). Synchronous Variability in the Southern Hemisphere Atmosphere, Sea Ice, and Ocean Resulting from the Annular Mode. *Journal of Climate*, 15(21), 3043–3057. [https://doi.org/10.1175/1520-0442\(2002\)015<3043:SVITSH>2.0.CO;2](https://doi.org/10.1175/1520-0442(2002)015<3043:SVITSH>2.0.CO;2)
- Haumann, F. A., Gruber, N., Münnich, M., Frenger, I., & Kern, S. (2016). Sea-ice transport driving Southern Ocean salinity and its recent trends. *Nature*, 537(7618), 89–92. <https://doi.org/10.1038/nature19101>
- Hauser, D. D. W., Whiting, A. V., Mahoney, A. R., Goodwin, J., Harris, C., Schaeffer, R. J., Schaeffer, R., Laxague, N. J. M., Subramaniam, A., Witte, C. R., Betcher, S., Lindsay, J. M., & Zappa, C. J. (2021). Co-production of knowledge reveals loss of Indigenous hunting opportunities in the face of accelerating Arctic climate change. *Environmental Research Letters*, 16, 095003. <https://doi.org/10.1088/1748-9326/ac1a36>
- Hay, S., & Kushner, P. J. (2024). The Relative Importance of Antarctic Sea Ice Loss within the Response to Greenhouse Warming. <https://doi.org/10.1175/JCLI-D-23-0524.1>
- Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., ... Thépaut, J.-N. (2020). The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, 146(730), 1999–2049. <https://doi.org/10.1002/qj.3803>
- Hinkelman, L. M., & Marchand, R. (2020). Evaluation of CERES and CloudSat Surface Radiative Fluxes Over Macquarie Island, the Southern Ocean. *Earth and Space Science*, 7(9), e2020EA001224. <https://doi.org/10.1029/2020EA001224>
- Hobbs, W. R., Bindoff, N. L., & Raphael, M. N. (2015). New Perspectives on Observed and Simulated Antarctic Sea Ice Extent Trends Using Optimal Fingerprinting Techniques. *Journal of Climate*, 28(4), 1543–1560. <https://doi.org/10.1175/JCLI-D-14-00367.1>

- Hobbs, W., Spence, P., Meyer, A., Schroeter, S., Fraser, A. D., Reid, P., Tian, T. R., Wang, Z., Linger, G., Doddridge, E. W., & Boyd, P. W. (2024). Observational Evidence for a Regime Shift in Summer Antarctic Sea Ice. *Journal of Climate*, 37(7), 2263–2275. <https://doi.org/10.1175/JCLI-D-23-0479.1>
- Holland, M. M., & Bitz, C. M. (2003). Polar amplification of climate change in coupled models. *Climate Dynamics*, 21(3), 221–232. <https://doi.org/10.1007/s00382-003-0332-6>
- Holland, M. M., Blanchard-Wrigglesworth, E., Kay, J., & Vavrus, S. (2013). Initial-value predictability of Antarctic sea ice in the Community Climate System Model 3. *Geophysical Research Letters*, 40(10), 2121–2124. <https://doi.org/10.1002/grl.50410>
- Holland, M. M., Landrum, L., Raphael, M., & Stammerjohn, S. (2017). Springtime winds drive Ross Sea ice variability and change in the following autumn. *Nature Communications*, 8(1), 731. <https://doi.org/10.1038/s41467-017-00820-0>
- Holland, M. M., Landrum, L., Raphael, M. N., & Kwok, R. (2018). The Regional, Seasonal, and Lagged Influence of the Amundsen Sea Low on Antarctic Sea Ice. *Geophysical Research Letters*, 45(20), 11,227–11,234. <https://doi.org/10.1029/2018GL080140>
- Hoskins, B. J., & Valdes, P. J. (1990). On the Existence of Storm-Tracks. https://journals.ametsoc.org/view/journals/atsc/47/15/1520-0469\1990\047\1854\oteost\2\0_co\2.xml
- Ionita, M. (2024). Large-scale drivers of the exceptionally low winter Antarctic sea ice extent in 2023. *Frontiers in Earth Science*, 12. <https://doi.org/10.3389/feart.2024.1333706>
- Jena, B., Kshitija, S., Bajish, C. C., Turner, J., Holmes, C., Wilkinson, J., Mohan, R., & Thamban, M. (2024). Evolution of Antarctic Sea Ice Ahead of the Record Low Annual Maximum Extent in September 2023. *Geophysical Research Letters*, 51(7), e2023GL107561. <https://doi.org/10.1029/2023GL107561>
- Josey, S. A., Meijers, A. J. S., Blaker, A. T., Grist, J. P., Mecking, J., & Ayres, H. C. (2024). Record-low Antarctic sea ice in 2023 increased ocean heat loss and storms. *Nature*, 636(8043), 635–639. <https://doi.org/10.1038/s41586-024-08368-y>
- Kato, S., Rose, F. G., Rutan, D. A., Thorsen, T. J., Loeb, N. G., Doelling, D. R., Huang, X., Smith, W. L., Su, W., & Ham, S.-H. (2018). Surface Irradiances of Edition 4.0 Clouds and the Earth's Radiant Energy System (CERES) Energy Balanced and Filled (EBAF) Data Product. <https://doi.org/10.1175/JCLI-D-17-0523.1>
- Kay, J. E., & Gettelman, A. (2009). Cloud influence on and response to seasonal Arctic sea ice loss. *Journal of Geophysical Research: Atmospheres*, 114(D18). <https://doi.org/10.1029/2009JD011773>

- Kidston, J., Taschetto, A. S., Thompson, D. W. J., & England, M. H. (2011). The influence of Southern Hemisphere sea-ice extent on the latitude of the mid-latitude jet stream. *Geophysical Research Letters*, 38(15). <https://doi.org/10.1029/2011GL048056>
- King, J. C., Marshall, G. J., Colwell, S., Arndt, S., Allen-Sader, C., & Phillips, T. (2022). The Performance of the ERA-Interim and ERA5 Atmospheric Reanalyses Over Weddell Sea Pack Ice. *Journal of Geophysical Research: Oceans*, 127(9), e2022JC018805. <https://doi.org/10.1029/2022JC018805>
- Koch, C. W., Brown, T. A., Amiraux, R., Ruiz-Gonzalez, C., MacCorquodale, M., Yunda-Guarin, G. A., Kohlbach, D., Loseto, L. L., Rosenberg, B., Hussey, N. E., Ferguson, S. H., & Yurkowski, D. J. (2023). Year-round utilization of sea ice-associated carbon in Arctic ecosystems. *Nature Communications*, 14(1), 1964. <https://doi.org/10.1038/s41467-023-37612-8>
- Komuro, Y., & Hasumi, H. (2003). Effects of surface freshwater flux induced by sea ice transport on the global thermohaline circulation. *Journal of Geophysical Research: Oceans*, 108(C2). <https://doi.org/10.1029/2002JC001476>
- Kostov, Y., Marshall, J., Hausmann, U., Armour, K. C., Ferreira, D., & Holland, M. M. (2017). Fast and slow responses of Southern Ocean sea surface temperature to SAM in coupled climate models. *Climate Dynamics*, 48(5), 1595–1609. <https://doi.org/10.1007/s00382-016-3162-z>
- Kromer, J. D., & Trusel, L. D. (2023). Identifying the Impacts of Sea Ice Variability on the Climate and Surface Mass Balance of West Antarctica. *Geophysical Research Letters*, 50(18), e2023GL104436. <https://doi.org/10.1029/2023GL104436>
- Kusahara, K., & Tatebe, H. (2025). Causes of the Abrupt and Sustained 2016–2023 Antarctic Sea-Ice Decline: A Sea Ice–Ocean Model Perspective. *Geophysical Research Letters*, 52(15), e2025GL115256. <https://doi.org/10.1029/2025GL115256>
- Kushner, P. J., Held, I. M., & Delworth, T. L. (2001). Southern Hemisphere Atmospheric Circulation Response to Global Warming. https://journals.ametsoc.org/view/journals/clim/14/10/1520-0442_2001_014_0001_shacrt_2.0.co_2.xml
- Landrum, L. L., & DuVivier, A. K. (2024). Sea ice is shrinking during Antarctic winter: Here's what it means for Earth's oceans and atmosphere. *Nature*, 636(8043), 578–579. <https://doi.org/10.1038/d41586-024-04078-7>
- Larson, J. G., Thompson, D. W. J., & Hurrell, J. W. (2024). Signature of the western boundary currents in local climate variability. *Nature*, 1–6. <https://doi.org/10.1038/s41586-024-08019-2>

- L'Heureux, M. L., & Thompson, D. W. J. (2006). Observed Relationships between the El Niño–Southern Oscillation and the Extratropical Zonal-Mean Circulation. <https://doi.org/10.1175/JCLI3617.1>
- Li, X., Cai, W., Meehl, G. A., Chen, D., Yuan, X., Raphael, M., Holland, D. M., Ding, Q., Fogt, R. L., Markle, B. R., Wang, G., Bromwich, D. H., Turner, J., Xie, S.-P., Steig, E. J., Gille, S. T., Xiao, C., Wu, B., Lazzara, M. A., ... Song, C. (2021). Tropical teleconnection impacts on Antarctic climate changes. *Nature Reviews Earth & Environment*, 2(10), 680–698. <https://doi.org/10.1038/s43017-021-00204-5>
- Libera, S., Hobbs, W., Klocker, A., Meyer, A., & Matear, R. (2022). Ocean-Sea Ice Processes and Their Role in Multi-Month Predictability of Antarctic Sea Ice. *Geophysical Research Letters*, 49(8), e2021GL097047. <https://doi.org/10.1029/2021GL097047>
- Lieser, J., Massom, R., Fraser, A., Haward, M., Heil, P., Lannuzel, D., Meiners, K., Melbourne-Thomas, J., Press, A., & Williams, G. D. (2014). Position analysis: Antarctic sea ice and climate change 2014. University of Tasmania. Report. <https://hdl.handle.net/102.100.100/495102>
- Liu, J., Zhu, Z., & Chen, D. (2023). Lowest Antarctic Sea Ice Record Broken for the Second Year in a Row. *Ocean-Land-Atmosphere Research*, 2, 0007. <https://doi.org/10.34133/olar.0007>
- Loeb, N. G., Doelling, D. R., Wang, H., Su, W., Nguyen, C., Corbett, J. G., Liang, L., Mitrescu, C., Rose, F. G., & Kato, S. (2018). Clouds and the Earth's Radiant Energy System (CERES) Energy Balanced and Filled (EBAF) Top-of-Atmosphere (TOA) Edition-4.0 Data Product. <https://doi.org/10.1175/JCLI-D-17-0208.1>
- Loeb, N. G., Mayer, M., Kato, S., Fasullo, J. T., Zuo, H., Senan, R., Lyman, J. M., Johnson, G. C., & Balmaseda, M. (2022). Evaluating Twenty-Year Trends in Earth's Energy Flows From Observations and Reanalyses. *Journal of Geophysical Research: Atmospheres*, 127(12), e2022JD036686. <https://doi.org/10.1029/2022JD036686>
- Lubin, D., & Massom, R. (Eds.). (2006). Sea ice. In *Polar Remote Sensing: Volume I: Atmosphere and Oceans* (pp. 309–728). Springer. https://doi.org/10.1007/3-540-30785-0_5
- Maksym, T., & Stammerjohn, S. (2025). The rise and fall of Antarctic sea ice: Large-scale variability. In *Sea Ice* (pp. 215–260). John Wiley & Sons, Ltd. <https://doi.org/10.1002/9781394213764.ch06>
- Mallet, M. D., Alexander, S. P., Protat, A., & Fiddes, S. L. (2023). Reducing Southern Ocean Shortwave Radiation Errors in the ERA5 Reanalysis with Machine Learning and 25 Years of Surface Observations. <https://doi.org/10.1175/AIES-D-22-0044.1>

- Marchi, S., Fichefet, T., Goosse, H., Zunz, V., Tietsche, S., Day, J. J., & Hawkins, E. (2019). Reemergence of Antarctic sea ice predictability and its link to deep ocean mixing in global climate models. *Climate Dynamics*, 52(5), 2775–2797. <https://doi.org/10.1007/s00382-018-4292-2>
- Marshall, G. J. (2003). Trends in the Southern Annular Mode from Observations and Re-analyses. https://journals.ametsoc.org/view/journals/clim/16/24/1520-0442\2003\016\4134_titsam\2.0.co\2.xml
- Mayer, J., Mayer, M., & Haimberger, L. (2021). Consistency and Homogeneity of Atmospheric Energy, Moisture, and Mass Budgets in ERA5. <https://doi.org/10.1175/JCLI-D-20-0676.1>
- Meehl, G. A., Arblaster, J. M., Bitz, C. M., Chung, C. T. Y., & Teng, H. (2016). Antarctic sea-ice expansion between 2000 and 2014 driven by tropical Pacific decadal climate variability. *Nature Geoscience*, 9(8), 590–595. <https://doi.org/10.1038/ngeo2751>
- Meehl, G. A., Arblaster, J. M., Chung, C. T. Y., Holland, M. M., DuVivier, A., Thompson, L., Yang, D., & Bitz, C. M. (2019). Sustained ocean changes contributed to sudden Antarctic sea ice retreat in late 2016. *Nature Communications*, 10(1), Article 1. <https://doi.org/10.1038/s41467-018-07865-9>
- Meier, W. N., Fetterer, F., Windnagel, A. K. & Stewart, J. S. (2021a). NOAA/NSIDC Climate Data Record of Passive Microwave Sea Ice Concentration. (G02202, Version 4). [Data Set]. Boulder, Colorado USA. National Snow and Ice Data Center. <https://doi.org/10.7265/efmz-2t65>.
- Meier, W. N., Fetterer, F., Windnagel, A. K. & Stewart, J. S. (2021b). Near-Real-Time NOAA/NSIDC Climate Data Record of Passive Microwave Sea Ice Concentration. (G10016, Version 2). [Data Set]. Boulder, Colorado USA. National Snow and Ice Data Center. <https://doi.org/10.7265/tgam-yv28>.
- Menéndez, C. G., Serafini, V., & Le Treut, H. (1999). The effect of sea-ice on the transient atmospheric eddies of the Southern Hemisphere. *Climate Dynamics*, 15(9), 659–671. <https://doi.org/10.1007/s003820050308>
- Meredith, M. P., Sommerkorn, M., Cassotta, S., Derksen, C., Ekaykin, A. A., Hollowed, A. B., Kofinas, G., Mackintosh, A. N., Muelbert, M. M. C., Melbourne-Thomas, J., Ottersen, G., Pritchard, H. D., & Schuur, E. A. G. (2019). Chapter 3: Polar Regions. In *The Ocean and Cryosphere in a Changing Climate: Summary for Policymakers* (pp. 3–3). Intergovernmental Panel on Climate Change. <https://research.monash.edu/en/publications/chapter-3-polar-regions>

- Minobe, S., Kuwano-Yoshida, A., Komori, N., Xie, S.-P., & Small, R. J. (2008). Influence of the Gulf Stream on the troposphere. *Nature*, 452(7184), 206–209. <https://doi.org/10.1038/nature06690>
- Minobe, S., Miyashita, M., Kuwano-Yoshida, A., Tokinaga, H., & Xie, S.-P. (2010). Atmospheric Response to the Gulf Stream: Seasonal Variations. <https://doi.org/10.1175/2010JCLI3359.1>
- Mioduszewski, J., Vavrus, S., & Wang, M. (2018). Diminishing Arctic Sea Ice Promotes Stronger Surface Winds. <https://doi.org/10.1175/JCLI-D-18-0109.1>
- Mo, K. C. (2000). Relationships between Low-Frequency Variability in the Southern Hemisphere and Sea Surface Temperature Anomalies. https://journals.ametsoc.org/view/journals/clim/13/20/1520-0442\2000\013\3599_rblfvi\2.0.co\2.xml
- Morioka, Y., Manabe, S., Zhang, L., Delworth, T. L., Cooke, W., Nonaka, M., & Behera, S. K. (2024). Antarctic sea ice multidecadal variability triggered by Southern Annular Mode and deep convection. *Communications Earth & Environment*, 5(1), 1–11. <https://doi.org/10.1038/s43247-024-01783-z>
- Morioka, Y., Zhang, L., Cooke, W., Nonaka, M., Behera, S. K., & Manabe, S. (2024). Role of anthropogenic forcing in Antarctic sea ice variability simulated in climate models. *Nature Communications*, 15(1), 10511. <https://doi.org/10.1038/s41467-024-54485-7>
- Ordoñez, A. C., Bitz, C. M., & Blanchard-Wrigglesworth, E. (2018). Processes Controlling Arctic and Antarctic Sea Ice Predictability in the Community Earth System Model. <https://doi.org/10.1175/JCLI-D-18-0348.1>
- Parkinson, C. L. (2004). Southern Ocean sea ice and its wider linkages: Insights revealed from models and observations. *Antarctic Science*, 16(4), 387–400. <https://doi.org/10.1017/S0954102004002214>
- Parkinson, C. L., & Cavalieri, D. J. (2012). Antarctic sea ice variability and trends, 1979–2010. *The Cryosphere*, 6(4), 871–880. <https://doi.org/10.5194/tc-6-871-2012>
- Parkinson, C. L. (2019). A 40-y record reveals gradual Antarctic sea ice increases followed by decreases at rates far exceeding the rates seen in the Arctic. *Proceedings of the National Academy of Sciences*, 116(29), 14414–14423. <https://doi.org/10.1073/pnas.1906556116>
- Pauling, A. G., Bitz, C. M., Smith, I. J., & Langhorne, P. J. (2016). The Response of the Southern Ocean and Antarctic Sea Ice to Freshwater from Ice Shelves in an Earth System Model. *Journal of Climate*, 29(5), 1655–1672. <https://doi.org/10.1175/JCLI-D-15-0501.1>

- Pellichero, V., Sallée, J.-B., Chapman, C. C., & Downes, S. M. (2018). The southern ocean meridional overturning in the sea-ice sector is driven by freshwater fluxes. *Nature Communications*, 9(1), 1789. <https://doi.org/10.1038/s41467-018-04101-2>
- Polvani, L. M., Banerjee, A., Chemke, R., Doddridge, E. W., Ferreira, D., Gnanadesikan, A., Holland, M. A., Kostov, Y., Marshall, J., Seviour, W. J. M., Solomon, S., & Waugh, D. W. (2021). Interannual SAM Modulation of Antarctic Sea Ice Extent Does Not Account for Its Long-Term Trends, Pointing to a Limited Role for Ozone Depletion. *Geophysical Research Letters*, 48(21), e2021GL094871. <https://doi.org/10.1029/2021GL094871>
- Polvani, L. M., Waugh, D. W., Correa, G. J. P., & Son, S.-W. (2011). Stratospheric Ozone Depletion: The Main Driver of Twentieth-Century Atmospheric Circulation Changes in the Southern Hemisphere. <https://doi.org/10.1175/2010JCLI3772.1>
- Previdi, M., & Polvani, L. M. (2014). Climate system response to stratospheric ozone depletion and recovery. *Quarterly Journal of the Royal Meteorological Society*, 140(685), 2401–2419. <https://doi.org/10.1002/qj.2330>
- Purich, A., & Doddridge, E. W. (2023). Record low Antarctic sea ice coverage indicates a new sea ice state. *Communications Earth & Environment*, 4(1), Article 1. <https://doi.org/10.1038/s43247-023-00961-9>
- Purich, A., & England, M. H. (2019). Tropical Teleconnections to Antarctic Sea Ice During Austral Spring 2016 in Coupled Pacemaker Experiments. *Geophysical Research Letters*, 46(12), 6848–6858. <https://doi.org/10.1029/2019GL082671>
- Purich, A., England, M. H., Cai, W., Sullivan, A., & Durack, P. J. (2018). Impacts of Broad-Scale Surface Freshening of the Southern Ocean in a Coupled Climate Model. *Journal of Climate*, 31(7), 2613–2632. <https://doi.org/10.1175/JCLI-D-17-0092.1>
- Raphael, M. N., & Handcock, M. S. (2022). A new record minimum for Antarctic sea ice. *Nature Reviews Earth & Environment*, 3(4), 215–216. <https://doi.org/10.1038/s43017-022-00281-0>
- Raphael, M. N., & Hobbs, W. (2014). The influence of the large-scale atmospheric circulation on Antarctic sea ice during ice advance and retreat seasons. *Geophysical Research Letters*, 41(14), 5037–5045. <https://doi.org/10.1002/2014GL060365>
- Raphael, M. N., Hobbs, W., & Wainer, I. (2011). The effect of Antarctic sea ice on the Southern Hemisphere atmosphere during the southern summer. *Climate Dynamics*, 36(7), 1403–1417. <https://doi.org/10.1007/s00382-010-0892-1>
- Rayner, N. A., Parker, D. E., Horton, E. B., Folland, C. K., Alexander, L. V., Rowell, D. P., Kent, E. C., & Kaplan, A. (2003). Global analyses of sea surface temperature, sea ice, and night

- marine air temperature since the late nineteenth century. *Journal of Geophysical Research: Atmospheres*, 108(D14). <https://doi.org/10.1029/2002JD002670>
- Rea, D., Elsbury, D., Butler, A. H., Sun, L., Peings, Y., & Magnusdottir, G. (2024). Interannual Influence of Antarctic Sea Ice on Southern Hemisphere Stratosphere-Troposphere Coupling. *Geophysical Research Letters*, 51(15), e2023GL107478. <https://doi.org/10.1029/2023GL107478>
- Riahi, K., van Vuuren, D. P., Kriegler, E., Edmonds, J., O'Neill, B. C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J. C., Kc, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., ... Tavoni, M. (2017). The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Global Environmental Change*, 42, 153–168. <https://doi.org/10.1016/j.gloenvcha.2016.05.009>
- Rintoul, S. R. (2018). The global influence of localized dynamics in the Southern Ocean. *Nature*, 558(7709), 209–218. <https://doi.org/10.1038/s41586-018-0182-3>
- Roach, L. A., Dörr, J., Holmes, C. R., Massonnet, F., Blockley, E. W., Notz, D., Rackow, T., Raphael, M. N., O'Farrell, S. P., Bailey, D. A., & Bitz, C. M. (2020). Antarctic Sea Ice Area in CMIP6. *Geophysical Research Letters*, 47(9), e2019GL086729. <https://doi.org/10.1029/2019GL086729>
- Roach, L. A., Mankoff, K. D., Romanou, A., Blanchard-Wrigglesworth, E., Haine, T. W. N., & Schmidt, Gavin. A. (2023). Winds and Meltwater Together Lead to Southern Ocean Surface Cooling and Sea Ice Expansion. *Geophysical Research Letters*, 50(24), e2023GL105948. <https://doi.org/10.1029/2023GL105948>
- Roach, L. A., & Meier, W. N. (2024). Sea ice in 2023. *Nature Reviews Earth & Environment*, 5(4), 235–237. <https://doi.org/10.1038/s43017-024-00542-0>
- Roach, L. A., & Meier, W. N. (2025). Sea ice in 2024. *Nature Reviews Earth & Environment*, 6(4), 252–254. <https://doi.org/10.1038/s43017-025-00662-1>
- Roemmich, D., & Gilson, J. (2009). The 2004–2008 mean and annual cycle of temperature, salinity, and steric height in the global ocean from the Argo Program. *Progress in Oceanography*, 82(2), 81–100. <https://doi.org/10.1016/j.pocean.2009.03.004>
- Rye, C. D., Marshall, J., Kelley, M., Russell, G., Nazarenko, L. S., Kostov, Y., Schmidt, G. A., & Hansen, J. (2020). Antarctic Glacial Melt as a Driver of Recent Southern Ocean Climate Trends. *Geophysical Research Letters*, 47(11), e2019GL086892. <https://doi.org/10.1029/2019GL086892>

- Sadai, S., Condrón, A., DeConto, R., & Pollard, D. (2020). Future climate response to Antarctic Ice Sheet melt caused by anthropogenic warming. *Science Advances*, 6(39), eaaz1169. <https://doi.org/10.1126/sciadv.aaz1169>
- Sahanatien, V., & Derocher, A. E. (2012). Monitoring sea ice habitat fragmentation for polar bear conservation. *Animal Conservation*, 15(4), 397–406. <https://doi.org/10.1111/j.1469-1795.2012.00529.x>
- Schemm, S. (2018). Regional Trends in Weather Systems Help Explain Antarctic Sea Ice Trends. *Geophysical Research Letters*, 45(14), 7165–7175. <https://doi.org/10.1029/2018GL079109>
- Schlosser, E., Haumann, F. A., & Raphael, M. N. (2018). Atmospheric influences on the anomalous 2016 Antarctic sea ice decay. *The Cryosphere*, 12(3), 1103–1119. <https://doi.org/10.5194/tc-12-1103-2018>
- Screen, J. A., & Blackport, R. (2019). How Robust is the Atmospheric Response to Projected Arctic Sea Ice Loss Across Climate Models? *Geophysical Research Letters*, 46(20), 11406–11415. <https://doi.org/10.1029/2019GL084936>
- Screen, J. A., & Simmonds, I. (2010a). Increasing fall-winter energy loss from the Arctic Ocean and its role in Arctic temperature amplification. *Geophysical Research Letters*, 37(16). <https://doi.org/10.1029/2010GL044136>
- Screen, J. A., & Simmonds, I. (2010b). The central role of diminishing sea ice in recent Arctic temperature amplification. *Nature*, 464(7293), 1334–1337. <https://doi.org/10.1038/nature09051>
- Serreze, M. C., Barrett, A. P., Stroeve, J. C., Kindig, D. N., & Holland, M. M. (2009). The emergence of surface-based Arctic amplification. *The Cryosphere*, 3(1), 11–19. <https://doi.org/10.5194/tc-3-11-2009>
- Sigmond, M., & Fyfe, J. C. (2010). Has the ozone hole contributed to increased Antarctic sea ice extent? *Geophysical Research Letters*, 37(18). <https://doi.org/10.1029/2010GL044301>
- Silber, I., Verlinde, J., Wang, S.-H., Bromwich, D. H., Fridlind, A. M., Cadetdu, M., Eloranta, E. W., & Flynn, C. J. (2019). Cloud Influence on ERA5 and AMPS Surface Downwelling Longwave Radiation Biases in West Antarctica. <https://doi.org/10.1175/JCLI-D-19-0149.1>
- Simpkins, G. R., Ciasto, L. M., Thompson, D. W. J., & England, M. H. (2012). Seasonal Relationships between Large-Scale Climate Variability and Antarctic Sea Ice Concentration. *Journal of Climate*, 25(16), 5451–5469. <https://doi.org/10.1175/JCLI-D-11-00367.1>

- Smith, D. M., Dunstone, N. J., Scaife, A. A., Fiedler, E. K., Copsey, D., & Hardiman, S. C. (2017). Atmospheric Response to Arctic and Antarctic Sea Ice: The Importance of Ocean–Atmosphere Coupling and the Background State. <https://doi.org/10.1175/JCLI-D-16-0564.1>
- Smith, D. M., Eade, R., Andrews, M. B., Ayres, H., Clark, A., Chripko, S., Deser, C., Dunstone, N. J., García-Serrano, J., Gastineau, G., Graff, L. S., Hardiman, S. C., He, B., Hermanson, L., Jung, T., Knight, J., Levine, X., Magnusdottir, G., Manzini, E., . . . Walsh, A. (2022). Robust but weak winter atmospheric circulation response to future Arctic sea ice loss. *Nature Communications*, 13(1), 727. <https://doi.org/10.1038/s41467-022-28283-y>
- Smith, D. M., Screen, J. A., Deser, C., Cohen, J., Fyfe, J. C., García-Serrano, J., Jung, T., Kattsov, V., Matei, D., Msadek, R., Peings, Y., Sigmond, M., Ukita, J., Yoon, J.-H., & Zhang, X. (2019). The Polar Amplification Model Intercomparison Project (PAMIP) contribution to CMIP6: Investigating the causes and consequences of polar amplification. *Geoscientific Model Development*, 12(3), 1139–1164. <https://doi.org/10.5194/gmd-12-1139-2019>
- Soci, C., Hersbach, H., Simmons, A., Poli, P., Bell, B., Berrisford, P., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Radu, R., Schepers, D., Villaume, S., Haimberger, L., Woollen, J., Buontempo, C., & Thépaut, J.-N. (2024). The ERA5 global reanalysis from 1940 to 2022. *Quarterly Journal of the Royal Meteorological Society*, 150(764), 4014–4048. <https://doi.org/10.1002/qj.4803>
- Song, J., Zhang, J., Du, S., Xu, M., & Zhao, S. (2025). Impact of Early Winter Antarctic Sea Ice Reduction on Antarctic Stratospheric Polar Vortex. *Journal of Geophysical Research: Atmospheres*, 130(3), e2024JD041831. <https://doi.org/10.1029/2024JD041831>
- Stammerjohn, S. E., Martinson, D. G., Smith, R. C., Yuan, X., & Rind, D. (2008). Trends in Antarctic annual sea ice retreat and advance and their relation to El Niño–Southern Oscillation and Southern Annular Mode variability. *Journal of Geophysical Research: Oceans*, 113(C3). <https://doi.org/10.1029/2007JC004269>
- Stuecker, M. F., Bitz, C. M., & Armour, K. C. (2017). Conditions leading to the unprecedented low Antarctic sea ice extent during the 2016 austral spring season. *Geophysical Research Letters*, 44(17), 9008–9019. <https://doi.org/10.1002/2017GL074691>
- Sun, L., Alexander, M., & Deser, C. (2018). Evolution of the Global Coupled Climate Response to Arctic Sea Ice Loss during 1990–2090 and Its Contribution to Climate Change. <https://doi.org/10.1175/JCLI-D-18-0134.1>
- Sun, S., & Eisenman, I. (2021). Observed Antarctic sea ice expansion reproduced in a climate model after correcting biases in sea ice drift velocity. *Nature Communications*, 12(1), 1060. <https://doi.org/10.1038/s41467-021-21412-z>

- Thompson, D. W. J., & Solomon, S. (2002). Interpretation of Recent Southern Hemisphere Climate Change. *Science*, 296(5569), 895–899. <https://doi.org/10.1126/science.1069270>
- Thompson, D. W. J., Solomon, S., Kushner, P. J., England, M. H., Grise, K. M., & Karoly, D. J. (2011). Signatures of the Antarctic ozone hole in Southern Hemisphere surface climate change. *Nature Geoscience*, 4(11), Article 11. <https://doi.org/10.1038/ngeo1296>
- Thompson, D. W. J., & Wallace, J. M. (2000). Annular Modes in the Extratropical Circulation. Part I: Month-to-Month Variability. <https://journals.ametsoc.org/view/journals/clim/13/5/1520-0442\2000\013\1000\amitec\2.0.co\2.xml>
- Tomas, R. A., Deser, C., & Sun, L. (2016). The Role of Ocean Heat Transport in the Global Climate Response to Projected Arctic Sea Ice Loss. <https://doi.org/10.1175/JCLI-D-15-0651.1>
- Trenberth, K. E., & Fasullo, J. T. (2010). Simulation of Present-Day and Twenty-First-Century Energy Budgets of the Southern Oceans. <https://doi.org/10.1175/2009JCLI3152.1>
- Turner, J., Comiso, J. C., Marshall, G. J., Lachlan-Cope, T. A., Bracegirdle, T., Maksym, T., Meredith, M. P., Wang, Z., & Orr, A. (2009). Non-annular atmospheric circulation change induced by stratospheric ozone depletion and its role in the recent increase of Antarctic sea ice extent. *Geophysical Research Letters*, 36(8). <https://doi.org/10.1029/2009GL037524>
- Turner, J., Holmes, C., Caton Harrison, T., Phillips, T., Jena, B., Reeves-Francois, T., Fogt, R., Thomas, E. R., & Bajish, C. C. (2022). Record Low Antarctic Sea Ice Cover in February 2022. *Geophysical Research Letters*, 49(12), e2022GL098904. <https://doi.org/10.1029/2022GL098904>
- Turner, J., Phillips, T., Marshall, G. J., Hosking, J. S., Pope, J. O., Bracegirdle, T. J., & Deb, P. (2017). Unprecedented springtime retreat of Antarctic sea ice in 2016. *Geophysical Research Letters*, 44(13), 6868–6875. <https://doi.org/10.1002/2017GL073656>
- Wang, G., Hendon, H. H., Arblaster, J. M., Lim, E.-P., Abhik, S., & van Rensch, P. (2019). Compounding tropical and stratospheric forcing of the record low Antarctic sea-ice in 2016. *Nature Communications*, 10(1), 13. <https://doi.org/10.1038/s41467-018-07689-7>
- Wang, H., Klekociuk, A. R., French, W. J. R., Alexander, S. P., & Warner, T. A. (2020). Measurements of Cloud Radiative Effect across the Southern Ocean (43° S–79° S, 63° E–158° W). *Atmosphere*, 11(9), 949. <https://doi.org/10.3390/atmos11090949>
- Wang, Z., Fraser, A. D., Reid, P., O’Farrell, S., & Coleman, R. (2024). Antarctic sea ice surface temperature bias in atmospheric reanalyses induced by the combined effects of sea ice and clouds. *Communications Earth & Environment*, 5(1), 552. <https://doi.org/10.1038/s43247-024-01692-1>

- Wills, R. C. J., Dong, Y., Proistosescu, C., Armour, K. C., & Battisti, D. S. (2022). Systematic Climate Model Biases in the Large-Scale Patterns of Recent Sea-Surface Temperature and Sea-Level Pressure Change. *Geophysical Research Letters*, 49(17), e2022GL100011. <https://doi.org/10.1029/2022GL100011>
- Yadav, J., Kumar, A., & Mohan, R. (2022). Atmospheric precursors to the Antarctic sea ice record low in February 2022. *Environmental Research Communications*, 4(12), 121005. <https://doi.org/10.1088/2515-7620/aca5f2>
- Zappa, G., Pithan, F., & Shepherd, T. G. (2018). Multimodel Evidence for an Atmospheric Circulation Response to Arctic Sea Ice Loss in the CMIP5 Future Projections. *Geophysical Research Letters*, 45(2), 1011–1019. <https://doi.org/10.1002/2017GL076096>
- Zhang, L., Delworth, T. L., Yang, X., Zeng, F., Lu, F., Morioka, Y., & Bushuk, M. (2022). The relative role of the subsurface Southern Ocean in driving negative Antarctic Sea ice extent anomalies in 2016–2021. *Communications Earth & Environment*, 3(1), 1–9. <https://doi.org/10.1038/s43247-022-00624-1>
- Zhang, L., Ren, X., Wang, C.-Y., Gan, B., Wu, L., & Cai, W. (2024). An observational study on the interactions between storm tracks and sea ice in the Southern Hemisphere. *Climate Dynamics*, 62(1), 17–36. <https://doi.org/10.1007/s00382-023-06894-5>
- Zhang, X., Deser, C., & Sun, L. (2021). Is There a Tropical Response to Recent Observed Southern Ocean Cooling? *Geophysical Research Letters*, 48(5), e2020GL091235. <https://doi.org/10.1029/2020GL091235>

Appendix A

Detrending Sensitivity

In Chapter 3 prior to most analysis, the long-term trend and mean seasonal cycle was removed. The long-term trend is calculated across the entire 1979–2024 period for all variables except for the CERES radiative flux data. We conducted a sensitivity analysis to test whether detrending across different periods or not at all would affect the results. Figure A.1 shows analogous plots to Figure 3.2b but after different methods of detrending. Figure A.1a is after the data has been detrended with a base period of 1979–2015, the period of sea-ice increases. Figure A.1b is after no trend has been removed from the data. Results are very similar to Figure 3.2b and indicate that major results are insensitive to choice of detrending method.

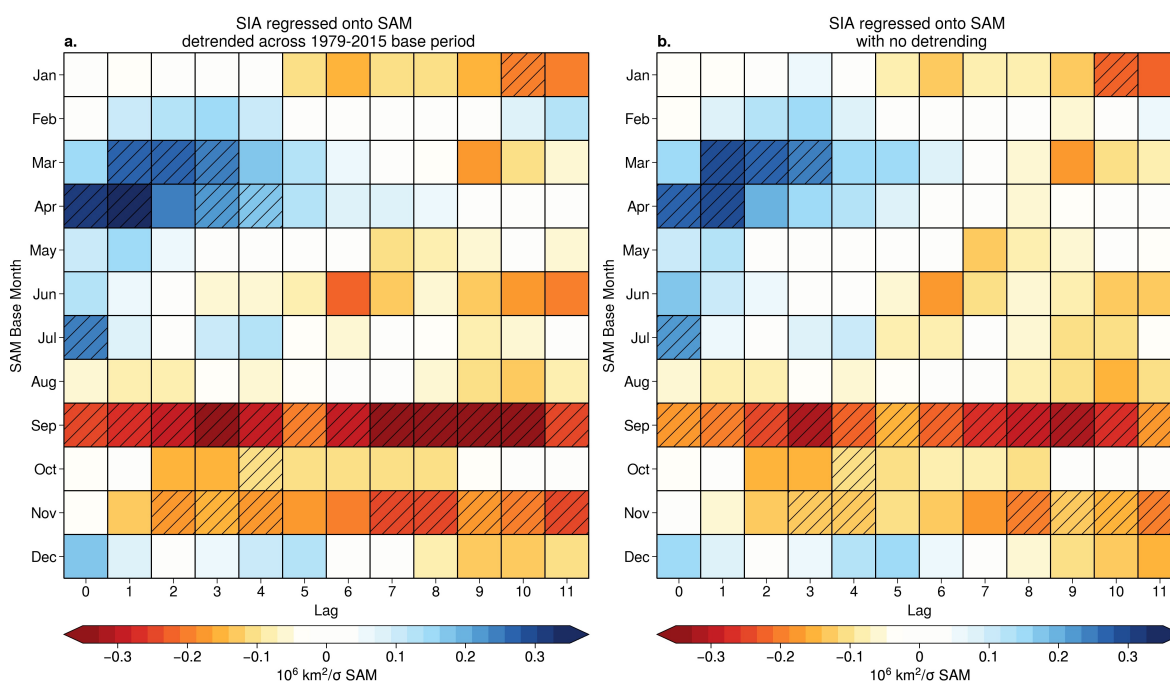


Figure A.1: As in Figure 3.2b but with different methods of detrending. (a) SIA and SAM time series linearly detrended with a base period of 1979–2015 prior to analysis and (b) SIA and SAM time series not linearly detrended prior to analysis.