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# Extreme Antarctic Sea Ice Loss Facilitated by Negative Shift of Southern Annular Mode

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**Key Points:**

- Extreme one-year declines in Antarctic sea ice, equal or greater than observed in 2015–2016, are rare in CMIP6 pre-industrial simulations
- Simulated abrupt sea-ice loss is typically linked to a negative Southern Annular Mode shift, similar to that observed in 2015–2016
- Most models show a sustained recovery of sea ice after abrupt loss without anthropogenic emissions, in contrast to recent observations

**Supporting Information:**

Supporting Information may be found in the online version of this article.

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**Abstract** Antarctic sea ice area exhibited an abrupt decline in 2015–2016, transitioning from a near record maximum state to a then-record minimum state. The underlying drivers are still being studied, raising questions whether this marks the onset of a long-term decline, or an isolated internal climate variability event. We identify extreme events in CMIP6 pre-industrial control simulations that are comparable to the observed extreme event in 2015–2016 and explore their atmospheric and oceanic drivers. Results show these events are rare but possible. The most robust association we find is between a negative Southern Annular Mode transition and extreme Antarctic sea ice loss. Most models show sea ice recovery after extreme loss, differing from the persistent decline observed in recent years. This contrast suggests anthropogenic forcing may now be playing a role. Our results underscore the role of internal variability while improving understanding of extreme events and their relevance for future sea ice predictability.

**Plain Language Summary** In 2016, Antarctic sea ice dropped sharply from a record high to a then record low, but the reasons behind it are still uncertain. Using pre-industrial climate model runs from the CMIP6 archive, which simulate the climate system without human influences, we investigate whether internal variability alone could explain this event and what key mechanisms might be involved, such as ocean temperatures, tropical weather patterns, and winds around Antarctica. In around 80 percent of the extreme sea ice loss events identified in pre-industrial model runs, ice-loss can be linked to a shift in wind patterns around Antarctica, where strong westerly winds weaken or reverse, allowing warmer air and oceanic conditions to reduce sea ice area. This highlights the important role of changing wind patterns in driving extreme sea ice losses. This research helps us understand sudden sea ice changes, including insights for the events in the last few years.

## 1. Introduction

In the two decades prior to 2014, the Antarctic sea ice area (SIA) experienced a steady increase, in contrast to the decrease in SIA predicted by climate models in a warming planet (Meehl et al., 2016). However, Antarctic SIA declined from a record high in 2014 to a then-record low in 2017, marking an unprecedented shift in the satellite era (Parkinson, 2019). While subsequent years have garnered significant attention, the largest year-on-year reduction in annual mean SIA occurred between 2015 and 2016, with SIA decreasing by 1.05 million km$^2$—approximately 10% of the total Antarctic SIA (Figure 1) (Turner et al., 2017; Schlosser et al., 2018; Z. Wang et al., 2019). Due to the relatively short satellite record (45 years) and the high internal variability of the southern high latitudes, it is challenging to fully quantify how exceptional this event truly is or to establish a clear baseline (Gilbert & Holmes, 2024). Diamond et al. (2024) examined the rarity of extreme Antarctic sea ice anomalies in the latest generation of climate models, estimating that a decline as severe as winter 2023 has a return period, that is, the expected average time between events of similar magnitude, of 2,650 years under internal variability alone, reducing to 580 years under strong climate change forcing. Similarly, Raphael et al. (2025) analyzed statistical reconstructions of Antarctic sea ice extent back to 1899, finding that the recent sequence of extreme summer minima is highly unlikely to have occurred in the 20th century. Their results suggest a possible shift in the Antarctic sea ice system, characterized by increased persistence of anomalies and a reduced tendency to return to its historical mean state.

However, the drivers of this rapid retreat in 2015–2016 are currently not well understood. It is therefore difficult to determine whether the sudden loss of sea ice signals the beginning of a long-term decline, as has been long

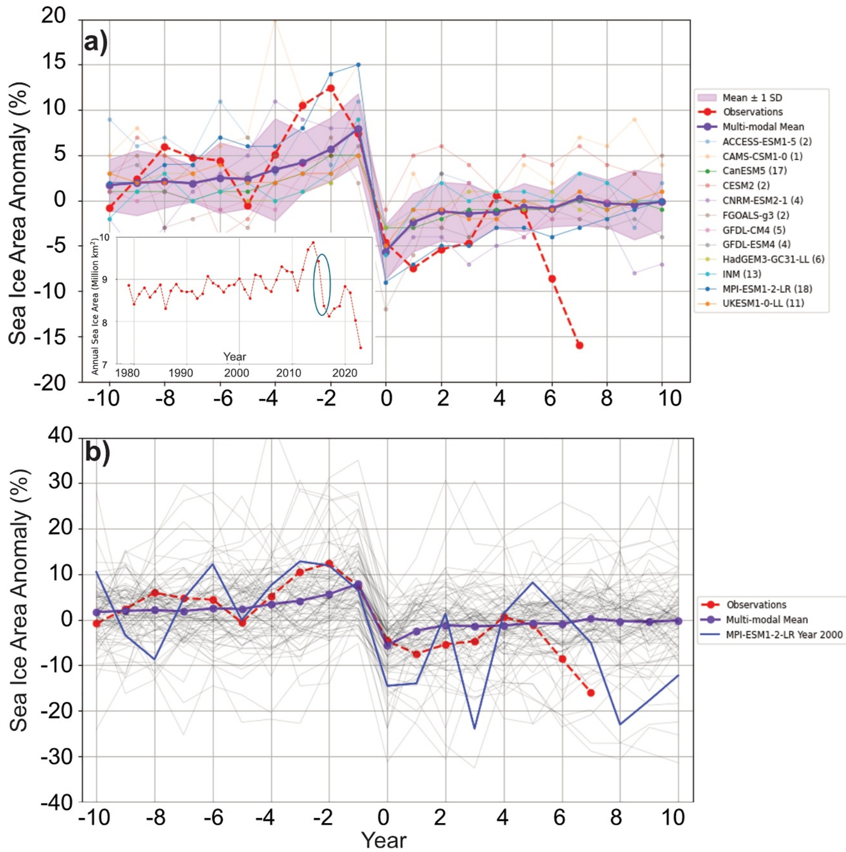


**Figure 1.** Observed and modeled annual mean Antarctic SIA anomalies (a) Antarctic SIA anomalies in satellite observations (dashed red line) and in CMIP6 model piControl simulations, in the years around an extreme loss event (shown as Year 0). Anomalies for the observations are calculated relative to the 1979–2023 mean Antarctic sea ice area, while model anomalies are computed as percentage deviations from each model's full-period climatology. The multi-model mean is shown in purple, the shaded region represents the multi-model mean ±1 standard deviation, and individual model ensemble means are as indicated in the legend. The inset graph shows the annual Antarctic SIA from satellite observations, highlighting the extreme sea ice loss event in 2015–2016 (blue ellipse). In panel (b), anomalies for the full ensemble of model simulations (gray lines), and a selected MPI-ESM1-2-LR simulation member r1i1p1f1 year 2000 (blue) are compared to the observations (red) and multi-model mean (purple) redrawn from panel (a).

anticipated by climate models (Eayrs et al., 2021; Roach et al., 2020; Yang et al., 2016), or was an isolated episode of internal climate variability (Holland et al., 2019). Thus, understanding these anomalies holds significance for evaluating climate models and informing future projections.

Two main schools of thought are commonly invoked to explain the recent Antarctic sea ice variability, namely: (a) subsurface warming of the Southern Ocean and (b) atmospheric variability and teleconnections, including large-scale modes such as the Southern Annular Mode (SAM), El Niño-Southern Oscillation (ENSO), and zonal wave 3 (ZW3) patterns, which can modulate regional wind and sea ice anomalies.

Warming of oceans can alter sea ice formation, extent and distribution (Hobbs et al., 2016). Southern Ocean warming can be attributed to increasing greenhouse gas concentrations, with ozone depletion and internal variability playing secondary roles (Hobbs et al., 2021; Swart et al., 2018). Purich and Doddridge (2023) highlights the significant role of subsurface Southern Ocean warming in driving the observed changes in Antarctic SIA, particularly 100–200 m depths in 2015. Meehl et al. (2019) highlight warmer upper ocean conditions in the Southern Ocean, driven by long-term changes in wind patterns and ocean circulation linked to the SAM and Interdecadal Pacific Oscillation. Atmospheric processes such as a positive SAM phase are proposed to promote sea ice reduction by bringing subsurface warm waters to the surface via Ekman transport (Purich et al., 2016).

Turning to the role of atmospheric variability, Haumann et al. (2016) and Kwok et al. (2017) identify the prominent role of meridional winds in driving sea ice trends across the satellite record, with zonal winds also contributing to regional ice redistribution. Ciasto et al. (2015) highlight a persistent ZW3 pattern and negative SAM, accompanied by significant easterly wind anomalies and record negative Indian Ocean Dipole mode index in 2015. These atmospheric anomalies led to a deepening of the Amundsen Sea Low and shifts in the mid-latitude westerlies, which in turn altered meridional heat and moisture transport. This resulted in anomalous surface pressure patterns, increased atmospheric moisture convergence, and enhanced precipitation over key regions, further influencing regional sea ice distribution and ocean-atmosphere interactions. Eayrs et al. (2021) highlight the importance of semi-annual shifts in the location and strength of the zonal winds encircling Antarctica. These winds impact the rate of autumn ice expansion and spring ice melt acceleration. SAM and ZW3 influence Antarctic sea ice through a combination of wind- and ocean-driven ice movement, as well as sea ice growth and melting (Raphael, 2007). Regional ice concentration changes result from alternating meridional ZW3-influenced winds and the interaction of SAM-related zonal winds with the ice edge, with their combined effects amplifying sea ice responses over western Antarctica when SAM-related mid-latitude winds weaken (Eabry et al., 2024). SAM and ENSO are key large-scale climate modes that influence the atmospheric circulation and sea surface temperature patterns in the Southern Ocean (Stammerjohn et al., 2008), where wind-driven advection of heat, moisture and momentum are the main mechanisms that drive sea ice growth and decline. When La Niña coincides with a positive SAM, it can result in enhanced SIA around Antarctica due to stronger circumpolar westerlies and colder sea surface temperatures. Conversely, when El Niño synchronizes with a negative SAM, the opposite effect occurs due to weakened westerlies, increased meridional heat transport, and warmer ocean and air temperatures in the Antarctic region (Clem et al., 2016). Therefore, the combination of positive or negative SAM phases with specific ENSO events can lead to different sea level pressure (SLP) responses and sea ice advection patterns (S. Wang et al., 2023).

Attributing trends in SAM and ENSO to anthropogenic forcing is challenging, as observed changes reflect both internal variability and external influences (Hobbs et al., 2016), and a limited observational record. A positive SAM trend in spring and summer has been linked to greenhouse gas emissions and ozone depletion (Christidis & Stott, 2015; G. J. Marshall et al., 2004), yet SAM alone does not fully explain sea ice variability (Lefebvre et al., 2004; Yu et al., 2011). Similarly, the deepening of the Amundsen Sea Low (ASL), associated with SAM and influenced by ozone depletion (England et al., 2016), aligns with anthropogenic forcing (Fogt & Wovrosh, 2015) but also falls within the range of internal variability (Turner et al., 2016). Understanding the relationship between anthropogenic forcing and internal variability involves several key considerations. Strong multi-decadal variability in high latitudes (Monselesan et al., 2015), combined with the transfer of heat to deeper oceans and the upwelling of colder waters (J. Marshall et al., 2015), results in a low signal-to-noise ratio in Antarctic sea surface temperatures (Hobbs et al., 2016). Additionally, stratospheric ozone may counteract the effects of greenhouse gas (J. Marshall et al., 2014; Polvani et al., 2021), while negative sea ice–ocean feedbacks can act to stabilize sea ice coverage (Kirkman & Bitz, 2011). These factors collectively mask anthropogenic signals and complicate the detection of their influence on Antarctic sea ice variability.

The challenge of attributing sea ice variability to anthropogenic forcing is further compounded by the limitations of the observational record, which represents only one realization of the climate system over a relatively short time period (45 years). To explore these questions within a longer and more comprehensive framework and timescale, we turn to piControl simulations from CMIP6, which isolate internal variability in the absence of external forcing and allow for a detailed examination of the internally-generated mechanism that could drive sea ice changes, as simulated by climate models. We can now look into how such extreme events could occur in the absence of human influence. We focus on 2015–2016 in contrast to existing literature, which focuses largely on 2016–2017 or 2022–2024. This is because 2015–2016 was both the largest annual mean decrease in the observed record and because it marked the beginning of the ongoing changes. The primary objective of this study is to investigate the potential drivers of extreme sea ice loss events by addressing the following key questions: (a) Can extreme sea ice loss events of similar magnitude to that observed in 2015–2016 occur solely due to internal variability, and if so, how likely are such events; and (b) What modes of atmospheric and oceanic variability are linked to these extreme events?

Through these investigations, this study aims to provide a deeper understanding of the mechanisms behind abrupt Antarctic sea ice loss events using pre-industrial control simulations. While we acknowledge the significance of the persistent record lows observed since 2016, our primary focus is on identifying the drivers of individual extreme events rather than their long-term persistence. These insights can help inform future projections of Antarctic sea ice.

## 2. Data Sets and Methods

*Observations*: We use SIA observations from the National Snow and Ice Data Center (NSIDC) (National Snow and Ice Data Center, 2025), covering the period from January 1979 to December 2024. The data set used was Sea Ice Index, Version 3, under the index of/NOAA/G02135/seaice-analysis/(Fetterer, 2017). All results refer to the annual mean. Anomalies are calculated relative to the climatological mean over the full satellite era (1979–2024).

*CMIP6 Models*: CMIP6 model data are from piControl simulations carried out with a total of 17 coupled climate models and the models are selected based on the availability of necessary variables. These simulations are integrations that include internal climate variability, with no anthropogenic influence, and thus provide a baseline for understanding internal climate variability. Each model provides a data set spanning a minimum of 450 years, leading to a combined analysis period of 13,903 years. We assessed the variability of annual-mean Antarctic SIA by comparing the 40-year standard deviation values (in million $km^2$) from each of the 17 CMIP6 models used in the analysis with that derived from satellite observations (1979–2023). This comparison is shown in Figure S1 in Supporting Information S1 and demonstrates that most models fall within the observed range, supporting the validity of including them in our analysis. This is to ensure a consistent basis for comparison when evaluating models against observations according to this bootstrapping methodology. For the CMIP6 models, anomalies of each variable are calculated relative to each model's own full-period climatology. With the exception of BCC-CSM, GFDL-CM4, and MPI-ESM1-2-LR models, which have higher standard deviation values, other models show values that are consistent with the observations. It has been tested that the removal of these three models from the results does not substantially change our results (not shown). Furthermore, shorter time series systematically underestimate the standard deviation, as a longer record is typically required to obtain a robust estimate of variability. Judging variability from a short observational record can therefore be misleading, especially when internal climate fluctuations occur on decadal or longer timescales. This highlights the importance of using long piControl simulations to characterize the full range of internal variability.

*Definition of Extreme Sea Ice Loss Events*: We here define an extreme sea ice event as any year that has more than 1.056 million $km^2$ SIA loss relative to the previous year, which corresponds to the largest observed loss event in 2016. As discussed later in the results section, changing the threshold by 10% in either direction does not substantially alter the results. A percentage-based approach is not used because percentage change in a model with low SIA would not necessarily indicate a significant loss event, making it less suitable for capturing extreme anomalies across different models. Following the identification of such events based on these criteria for each model, a composite analysis is performed to explore the atmospheric and oceanic variables leading up to these events. This analysis focuses on the year preceding the event year and the event year itself, as it allows for a comparison of pre-existing conditions with the event year to identify the mechanisms that drive sea ice changes. The multi-model mean of all events across the models is calculated by averaging the events from each model, ensuring equal weighting for each model in the analysis. Additionally, a weighted average of the square root of the occurrence of the extreme events for the models was used to combine all the models into one summary plot for all variables, similar to the approach of England et al. (2025). This approach helps to capture the relative importance of each model's contribution to the overall pattern and represents a compromise between reducing spurious variability, which would encourage giving each event an equal weight, and preventing individual models from dominating the results, which would push for equal weighting of each model. However, we emphasize that our conclusions remain largely unchanged even if all members are weighted equally.

To assess sea ice anomalies and extreme sea ice loss events, we identify extreme sea ice loss years in each model. Anomalies are calculated by comparing the sea ice area of the extreme event year to the long-term mean sea ice area for the entire piControl simulation, expressed as a percentage difference. This percentage-based calculation is used only for the analysis and comparison of sea ice responses across models with differing baseline climates, not for event selection.

*Calculation of SAM and Nino 3.4*: Motivated by findings from previous studies, such as Eayrs et al. (2021), we calculate the SAM and Nino 3.4 anomaly to analyze large-scale local and tropical drivers respectively. The SAM index is calculated as the normalized difference between the zonal mean pressure anomalies at 40°S and 65°S using the method of Gong and Wang (1999). For the Niño 3.4 index, sea surface temperature (SST) data is extracted over the Niño 3.4 region (5°S–5°N, 190°–240°E) (Schneider et al., 2013). For both SAM and Niño 3.4 indices, they are calculated as annual means, which is comparable to the annual SIA changes investigated in this study.

## 3. Results

### 3.1. Frequency and Time Evolution of Events

We start by identifying the likelihood and pattern of the extreme events in piControl runs of CMIP6 models and answer the first question posed in our introduction: Can extreme sea ice loss events of similar magnitude occur solely due to internal variability? If no extreme sea ice loss events are found in these models, the conclusion would be straightforward: such events are not likely to be possible without human influences.

Using the threshold definition provided in Section 2 (Data Sets and Methods), we identify a total of 87 extreme sea ice loss events across 12 out of the 17 climate models, thus demonstrating that extreme sea ice loss events can occur due to internal variability alone, although their frequency and spatial patterns vary across models and events, as shown in Figure 1a and Table S1 in Supporting Information S1. In addition, we find that changing the threshold by 10% does not impact the results significantly by testing one of the most important variables, surface westerly wind speed anomaly (Figure S2 and Tables S2 and S3 in Supporting Information S1). This suggests that the threshold approach is robust and can be relied upon to capture consistent patterns in the models.

The multi-model average shows a build-up of sea ice identifiable 10 years prior to the extreme sea ice loss year, with an accelerated rate a few years prior to the event year, with one model run showing a similar trend to observations. The build-up of sea ice is also apparent in observations, seen in the inset of Figure 1a during the period of 2000–2014. Importantly, the observed SIA trends fall within the models' spread, indicating that the models are robust in capturing the behavior of sea ice anomalies and their associated variability. This agreement lends confidence to the models' ability to replicate the processes driving extreme sea ice loss events.

Next, we compare the time series of observation (red) and the MPI-ESM1-2-LR member r1i1p1f1 in (Figure 1b). This event is chosen because a second drop of a similar magnitude occurs within the 10 year period of the initial event year. This comparison highlights the capacity of the model to simulate successive extreme events within a relatively short timescale, consistent with the observed variability, although it must be noted that this model has excessively high interannual variability.

Having established that extreme sea ice loss events occur in piControl model runs, we can now examine the regional and temporal evolution of these events, focusing on the build-up and subsequent loss of sea ice. In the year preceding an extreme event, the models simulate a robust positive anomaly in sea ice concentration (SIC) across the Antarctic, with the most pronounced positive anomaly occurring in the Weddell and Ross Sea regions (Figures 2a and 2b). During the event year, approximately three-quarters of the modeled events exhibit substantial sea ice loss in the Weddell Sea, aligning with observational records from 2015/2016. Interestingly, about one-fifth of the events show notable sea ice positive anomalies in the Amundsen-Bellingshausen Sea (ABS), even as other regions exhibit substantial losses. This feature is also reflected in observations (Figure S3 in Supporting Information S1). However, the sea ice positive anomaly does not fall within the hatched regions, indicating the models do not fully agree on the sign of change in this region.

### 3.2. Oceanic and Atmospheric Precursors

We now investigate the second question, which is to look at the modes of atmospheric and oceanic variability potentially contributing to these extreme events. The El Niño warming event in the central equatorial Pacific Ocean is a prominent feature in the weighted mean figure (Figure 2d). During the event year, surface temperature warming is particularly localized in the Weddell and Ross Sea regions, contrasting with an overall cooling phase observed in the preceding year (Figure 2c). SLP (shown as contour lines) also transitioned from negative to positive pressure anomalies around the Southern Ocean near the continent. A cooling event is simulated in the ABS. Additionally, when we examine the westerly zonal winds, a strengthening of the winds in the year preceding the event year (Figure 2e) can be observed, which rapidly transitions to a weakening of the winds during the event year (Figure 2f). This can be understood as an equator-ward shift of the strongest zonal winds, and corresponds to a positive SAM phase (SAM Index = 1.04 ± 0.48) in the preceding year and a negative SAM phase (SAM

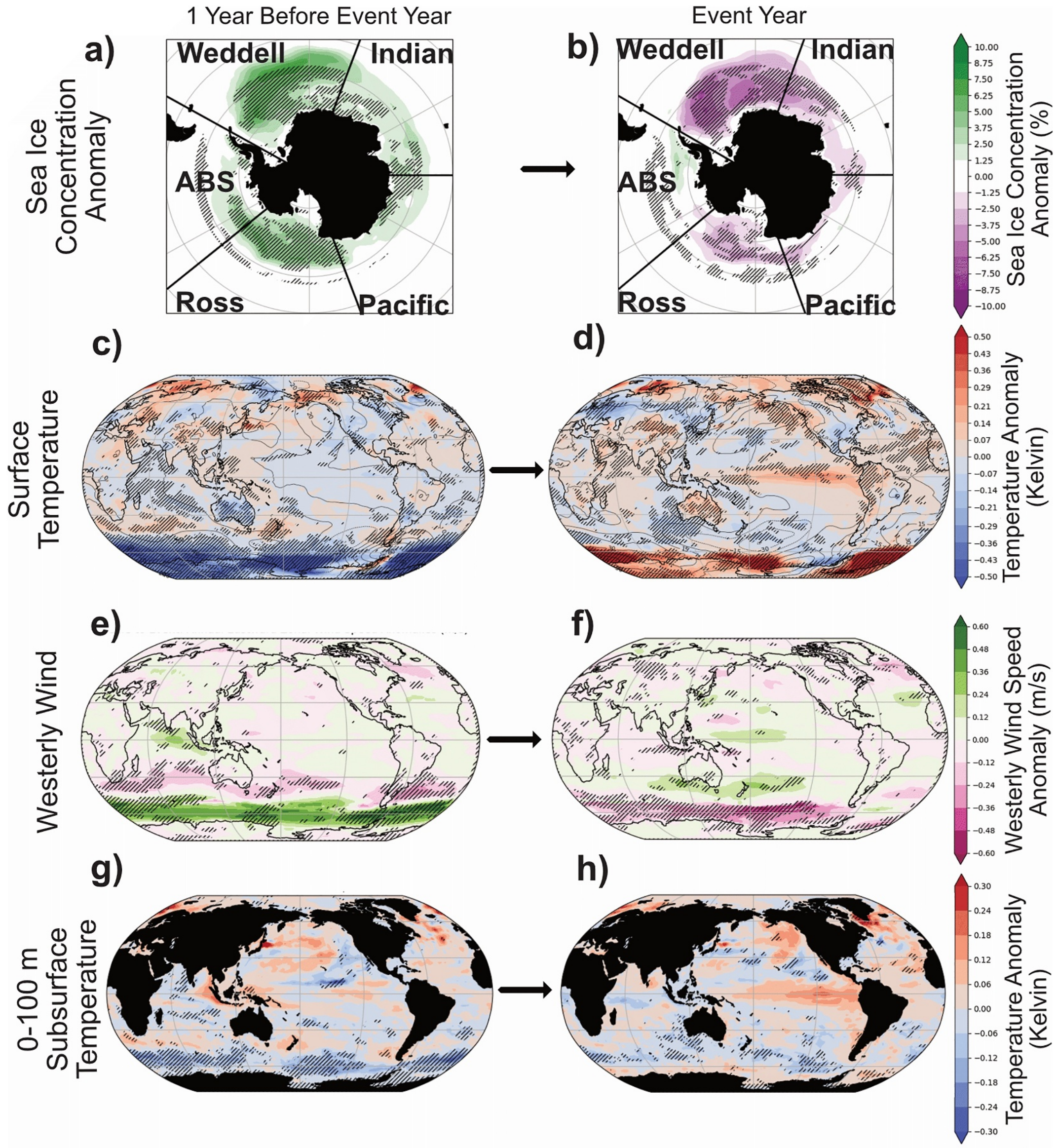


**Figure 2.** Multi-model mean anomalies of key atmospheric, oceanic and sea ice variables simulated during the 1 year before the event (left) and the event year (right), showing (a, b) Antarctic SIC; (c, d) surface temperature (K), with sea level pressure anomalies shown as contour lines; (e, f) westerly winds (m/s) and (g, h) ocean temperature over the top 100 m (K). Hatching indicates regions where 80% of models agree on the sign of the anomaly. The combined sector of Amundsen and Bellingshausen Sea is abbreviated as ABS.

Index = −0.35 ± 0.45) in the event year across the models. This suggests that it is not the final state of the SAM that matters most, but rather the transition itself, as the annual differences in wind patterns appear to drive the most significant sea ice changes. We note that while this analysis is conducted using annual-mean values, the limitations of this approach are addressed in the discussion. In observations, the SAM index similarly dropped from +4.13 in 2015 to +1.67 in 2016, a decrease of 2.46, which correspnding to roughly 1.1 standard deviations greater than the mean internanual variability (Gong & Wang, 1999). While this remains within the positive phase overall, the magnitude of the drop ranks among the larger year-to-year SAM changes in the satellite record. This supports our interpretation that rapid SAM transitions, rather than their absolute phase, may be a key contributor to driving extreme Antarctic sea ice loss events. We note, however, that observed SAM values tend to be more positive than those in the piControl simulations, reflecting a long-term positive trend in observations. Our focus here is on the magnitude of the change, rather than the baseline state, which allows for more consistent comparison across models and observations.

In the upper 100 m of the Southern Ocean, we observe a general cooling in the waters surrounding Antarctica during the year preceding the event. There is a localized warming of up to 0.18 K in the Weddell and Ross Sea regions during the event year, a pattern consistent across all models (Figures 2g and 2h). However, the subsurface temperature in the 100–500 m of the Southern Ocean remains largely unchanged, as shown in Figure S4 in Supporting Information S1. The patterns from the subsurface ocean temperature from the top 100 m is mimicking changes in the atmospheric variables, where there is a warming ocean temperature anomaly at the east pacific basin. These findings highlight the relatively modest role of oceanic subsurface variability in driving extreme sea ice loss events in piControl runs, suggesting that, in these simulations at least, near-surface ocean temperatures are largely influenced by atmospheric conditions. An assessment of the strengths and weaknesses of the analysis of annual sea ice anomalies is provided later in the discussion.

Our analysis reveals distinct patterns in the relationship between SAM and ENSO, and Antarctic SIA during extreme events. Approximately 80% of these events are marked by a transition towards a negative SAM (Figures 3a–3c), as highlighted by the clustering of data points in the bottom two quadrants. This is reflected in the clear clustering of data points in the bottom two quadrants of the SAM change versus SIA anomaly plot. These findings reinforce our earlier point that it is not the change in the SAM phase that matters most, but rather the negative shift. However, we also note that a small number of events are associated with a positive change in SAM, indicating that this is not a strictly necessary condition and that other mechanisms can occasionally drive such extremes.

In contrast, only about 50% of events show a transition towards a positive Niño 3.4 index, indicating a less consistent relationship between ENSO phases and extreme sea ice loss events (Figures 3b and 3c). This suggests a less consistent relationship between ENSO phase transitions and sea ice anomalies, highlighting the limited role of ENSO in driving annual-scale extremes in these piControl simulations. Taken together, the panels in Figure 3 illustrate that while both SAM and ENSO can influence sea ice variability, SAM transitions exhibit a stronger and more systematic association with extreme sea ice loss events in the climate models studied here.

## 4. Discussion

Our findings highlight the potential role of internal climate variability in driving extreme sea ice loss events, emphasizing that events as extreme as that observed in 2015–2016 can occur without the influence of anthropogenic forcing. While the exact mechanisms vary between simulated cases, these events are rare phenomena within the piControl runs.

Our key novel finding is that it is not merely the presence of a negative SAM phase that is associated with extreme Antarctic sea ice loss, but rather a negative change in the SAM, that is, a rapid decline in SAM from one year to the next, regardless of whether the phase remains positive. Bonan et al. (2024) support this, as they demonstrate that abrupt Antarctic sea ice declines are linked to atmospheric circulation changes, specifically a weakening of the circumpolar westerlies. This weakening reduces northward Ekman transport, leading to surface ocean warming through a shoaling of the mixed layer, thus creating conditions that favor rapid sea ice loss. Southerly and easterly wind anomalies linked to negative SAM can shift sea ice northwards, creating openings in the ice pack that enhance ocean warming and basal melting. Additionally, it can facilitate abnormal poleward heat transport in the Ekman layer, further contributing to ice melting (Blanchard-Wrigglesworth et al., 2021). Overall, the results highlight the role of large-scale climatic patterns in shaping the occurrence and intensity of extreme sea ice loss events. The consistent reproduction of these patterns across numerous models underscores their importance for understanding future changes in sea ice cover.

While the results indicate that negative changes in SAM are more consistently associated with extreme Antarctic sea ice events compared to transitions in Niño 3.4, it is important to consider differences in CMIP6 models' representation of ENSO and SAM. According to Table TS4 in the IPCC AR6 Technical Summary, CMIP6 models generally reproduce SAM with high performance, while ENSO performance is rated as medium (Arias et al., 2021). The lower performance of CMIP6 models in simulating ENSO, relative to SAM, may contribute to the weaker and less consistent relationship between ENSO variability and Antarctic sea ice anomalies across the models. Furthermore, ENSO's impacts on sea ice are often regionally confined (Yuan, 2004), with the strongest

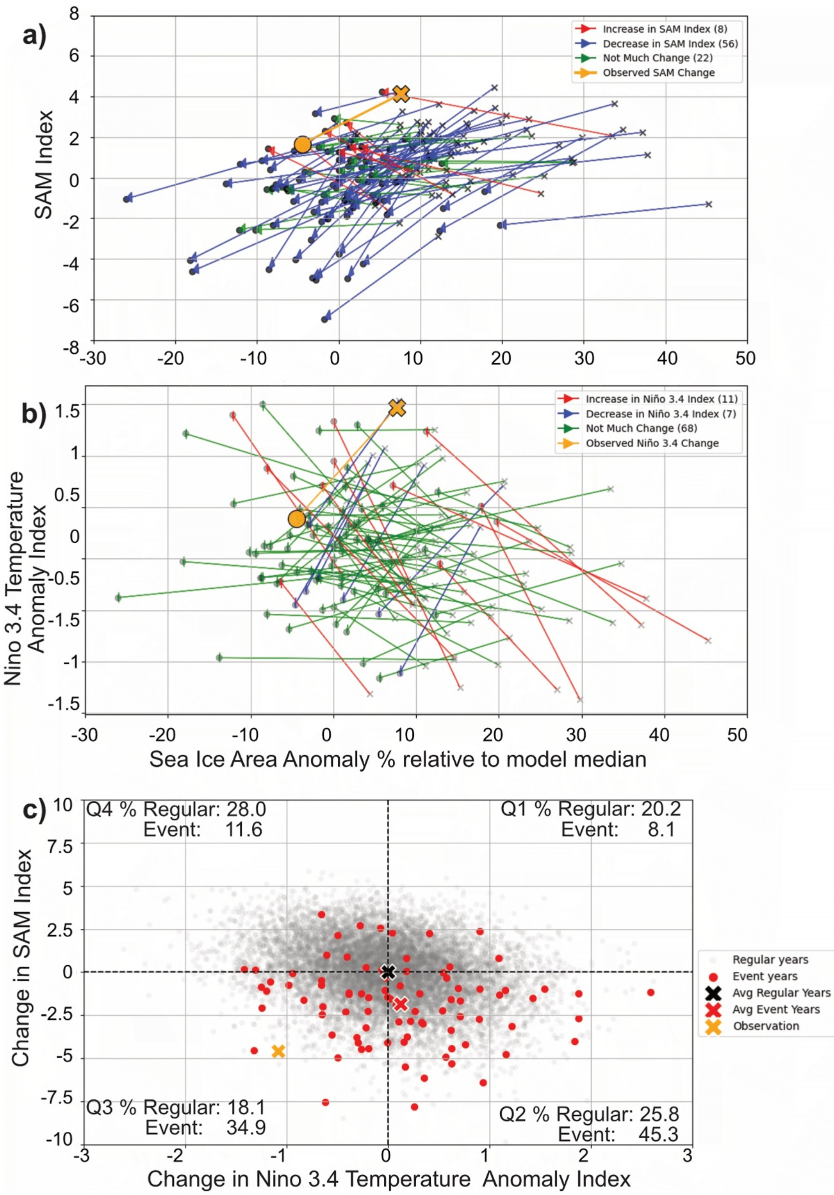


**Figure 3.** Comparison of relative SIA percentage (relative to model median area) change against climate indices (Nino 3.4 and SAM) changes for all events in models and observations. (a) Change between relative SIA percentage and normalized SAM index: Scatter points represent SAM indices for 1 year before event (crosses) and event years (dots), with color-coded arrows (red for decreasing, blue for increasing, green for change less than 1 standard deviation of normalized values) showing transitions. The orange cross and circle highlights observed SAM index changes between 2015 and 2016. (b) As (a) but for relative SIA percentage and Nino 3.4 index. Legends provide arrow counts corresponding to directional changes in the indices. (c) Scatter plot of SAM index versus Nino 3.4 temperature anomaly index for all years (gray), event years (red), all-year average (black cross), event year average (red cross) and 2015–2016 observations (orange cross). The numbers next to Q1–4 represents the percentage of regular and event years in each quadrant.

impacts in the western antarctic region and the antarctic peninsula. To partially address this issue, correlation tests were conducted between ENSO and SAM against Antarctic SIA across our model ensemble (results not shown). We found that correlations with ENSO were generally weak, ranging from −0.25 to +0.02 and no clustering around a consistent range of values, indicating a limited and inconsistent influence of ENSO on sea ice in these simulations. On the other hand, 8 out of 12 models show consistent positive relationship and SAM values cluster between 0.10 and 0.20. This suggests a reasonably consistent positive relationship between SAM and SIA across models, with higher SAM associated with more sea ice. In models, ENSO phase transitions may also occur more gradually or with reduced magnitude compared to observations (e.g., 2015–2016), reducing the robustness of one-year shifts and their associated sea ice responses. The representation of ENSO magnitude, frequency, or associated teleconnection patterns in CMIP6 models may explain their apparently weaker influence on the Southern Hemisphere high latitudes. For instance, ENSO related teleconnections to polar regions in models have been shown to occur in different locations compared to observations, leading to their underestimation (Fang et al., 2024; Hu et al., 2023). It is plausible that such spatial mismatches also affect the sea ice response to ENSO in our model analysis.

However, the consistent SAM transitions observed across all models, regardless of their ENSO representation, underscore its dominant role in driving widespread sea ice loss. While SAM plays a more direct and reliable role in driving sea ice variability, it alone is not sufficient to fully explain the occurrence of these extreme events. Notably, there are instances where negative changes in SAM occur without significant sea ice declines and events where sea ice declines coincide with positive SAM changes. Neither SAM nor ENSO alone can account for the full range of observed variability, highlighting the importance of considering additional atmospheric and oceanic processes, such as zonal wave patterns or localized wind anomalies, to better understand the drivers of extreme Antarctic sea ice anomalies. We do not find evidence of a build-up of heat at the subsurface ocean layers contributing to extreme sea ice loss in CMIP6 model pi-control runs. This does not imply that extreme sea ice loss events were unaffected by sub-ocean temperature changes; rather, it indicates that ocean heat build-up in the models is not a significant driver of ice loss events caused by internal variability alone according to models. Regarding the robustness of CMIP6 model simulations in representing sub-surface ocean temperatures in relation to observations, recent assessments suggest that CMIP6 models are improving in their ability to simulate sub-surface ocean conditions (Oh et al., 2023). We acknowledge that CMIP6 models still exhibit biases in subsurface processes and ocean–sea ice coupling, and that PI-control simulations are not directly comparable to recent observed events due to the absence of external forcing. As such, while subsurface temperature is not identified as a primary driver of sea ice loss in the simulations we have analysed here, this does not preclude its importance in the real world.

The lack of sub-surface heat build-up does not contradict the conclusions of Purich and Doddridge (2023). On the contrary, it aligns with their argument that for subsurface warming to significantly contribute to sea ice loss, anthropogenic warming must play a crucial role. Moreover, observational analyses indicate that during the 2015/2016 event, surface and mixed-layer temperatures exhibited a quadrupole pattern consistent with ENSO-related heat flux anomalies (Blunden et al., 2017). However, substantial observational gaps remain in the Southern Ocean, particularly beneath perennial sea ice, continental shelves, and at depths below 2,000 m, which limits our ability to fully constrain subsurface temperature variability and to fully understand its role in sea ice loss events even based on observational analysis.

Our analysis represents the average response across a large number of events in climate models, minimizing sampling uncertainty. The use of annual averages provides a simplified and consistent framework for comparing diverse model simulations and isolating broad-scale trends. This approach may smooth out smaller-scale processes, such as seasonal patterns, that influence Antarctic sea ice variability. While our analysis highlights robust patterns and relationships, it is important to note that short-term fluctuations, like shifts in zonal winds, zonal wave 3 patterns, and ocean-ice interactions, play a crucial role in sea ice evolution. Boehm et al. (2025) shows that the influence of the SAM on Antarctic SIA exhibits strong seasonal dependencies, with positive SAM anomalies around the time of sea ice maximum leading to reduced SIA in the following year, whereas during the sea ice minimum, they contribute to subsequent increases in SIA. These findings suggest that seasonal timing plays a critical role in the persistence and impact of SAM-related anomalies. Our use of annual means simplifies this complexity but captures the net-integrated effect of these processes across a large ensemble of events.

Our findings carry important implications for understanding future Antarctic sea ice behavior in a warming climate. The CMIP6 models generally do not reproduce the persistent record-low sea ice conditions observed in recent years, such as those in 2022–2023. This discrepancy suggests that long-term anthropogenic warming may be playing a growing role in shaping recent sea ice trends. One possible implication is that, as the ocean and atmosphere continue to warm via subsurface heat accumulation and surface warming, Antarctic sea ice may become increasingly sensitive to atmospheric variability, such as SAM-related circulation changes. In this context, our finding that extreme sea ice loss events are strongly linked to year-to-year negative shifts in the SAM highlights a potential mechanism through which anthropogenic forcing could amplify future sea ice extremes.

In light of the record-low sea ice extent observed in 2022–2023, our results imply that such a rapid recurrence may exceed the bounds of internal variability in climate models alone. Rather, it likely reflects a complex interplay between internal ocean–atmosphere dynamics and external forcing. Further investigation into these interactions is essential for improving future projections and anticipating the ecological and climatic consequences of abrupt sea ice decline.

## Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

## Data Availability Statement

The data sets analyzed in this study are all publicly available. Data for CMIP6 models can be obtained from the Earth Systems Grid Federation (ESGF) website (https://aims2.llnl.gov/search). NSIDC annual mean total Antarctic SIA data can be downloaded from https://noaadata.apps.nsidc.org/NOAA/G02135/ and under the sub directory seaice_analysis The file used is `Sea_Ice_Index_Monthly_Data_by_Year_G02135_v3.0.xlsx`. Individual CMIP6 model data sets used in this study are listed in Table S1 in Supporting Information S1 and can be accessed on the ESGF portal via the URL https://aims2.llnl.gov/search.

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