

The Southern Annular Mode and its relationship with Antarctic temperature in contrasting future storylines

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Supplementary Material

S1 Summary of storyline methodology

A regression framework incorporating the two chosen remote drivers is used to develop the storylines. Multiple Linear Regression (MLR) equations were computed for both seasons, based on the framework of Zappa and Shepherd (2017) and detailed further in Williams et al. (2024). For austral winter and summer the equations are given in Eqs. (S1) and (S2), respectively:

$$P_{xm} = a_x + b_x \left(\frac{\Delta \text{SIE}_{\text{JJA}}}{\Delta T} \right)'_m + c_x \left(\frac{\Delta \text{U50}_{\text{JJA}}}{\Delta T} \right)'_m + d_{xm} \quad (\text{S1})$$

$$P_{xm} = a_x + b_x \left(\frac{\Delta \text{SIE}_{\text{DJFM}}}{\Delta T} \right)'_m + c_x \left(\frac{\Delta \text{U50}_{\text{ND}}}{\Delta T} \right)'_m + d_{xm} \quad (\text{S2})$$

where P_{xm} represents the pattern of climate response of a target parameter (e.g., SAT) in which x refers to a model grid-point and m to a model. The term a_x is the global-warming — here defined as the difference in annual-mean global-mean temperature between the future and present periods — scaled multimodel mean (MME) response of the target parameter; b_x is the regression coefficient calculated from the standardised anomaly in the SIE change predictor (also scaled to global-warming) for each model with respect to the MME scaled response, indicated by the vertical dash ‘; and c_x is an equivalent term for the U50 predictor. ΔT represents the individual model global-warming (as defined above) and d_{xm} constitutes other influences on P_{xm} not portrayed by the MLR model. The regression coefficients (b_x and c_x) vary spatially whereas values in parentheses fluctuate across models: thus, collectively, all terms vary both spatially and between models. For calculating any MME value, all fields were bilinearly interpolated to a common grid, equivalent to $\sim 2.8^\circ$ horizontal resolution.

To obtain each storyline the regression coefficients for each remote driver from Eqs. (S1) and (S2) were multiplied by a storyline coefficient S , chosen to correspond to the 80% confidence region of the joint distribution in the two drivers (see black ellipse in Fig. S1). Hence the mathematical derivation of the four possible storylines can be written as:

$$P_x = a_x \pm b_x S \pm c_x S \quad (\text{S3})$$

S is multiplied by each regression coefficient at each grid point and added/subtracted from the MME response of the target variable to derive four plausible storylines for the pattern of response P_x (see Table 1 in the main text). The responses of the two drivers are of the same sign in each storyline for pair A (+ +) and D (– –) but of opposing sign for each storyline in pair B (+ –) and C (– +) relative to the MME. However, as one driver is negative in sign (SIE loss) and one is positive (SPV strengthening), the changes in the two drivers are actually the same (opposite) in direction for Storylines B and C (Storylines A and D). Thus, in Fig. S1 storyline pair B and C are shown as red dots where the ellipse intersects a hypothetical line $(\Delta \text{SIE}/\Delta T) = (\Delta \text{SPV}/\Delta T)$ while storyline pair A and D are shown as blue dots where the ellipse intersects a hypothetical line $(\Delta \text{SIE}/\Delta T) = -(\Delta \text{SPV}/\Delta T)$. We note from Fig. S1 that the distribution of the model predictor responses is essentially random, as expected given the chosen drivers are uncorrelated across the models. Thus, the number of candidate models for each storyline,

those within the dashed lines in Fig. S1 (red for Storylines B and C, blue for A and D), varies markedly.

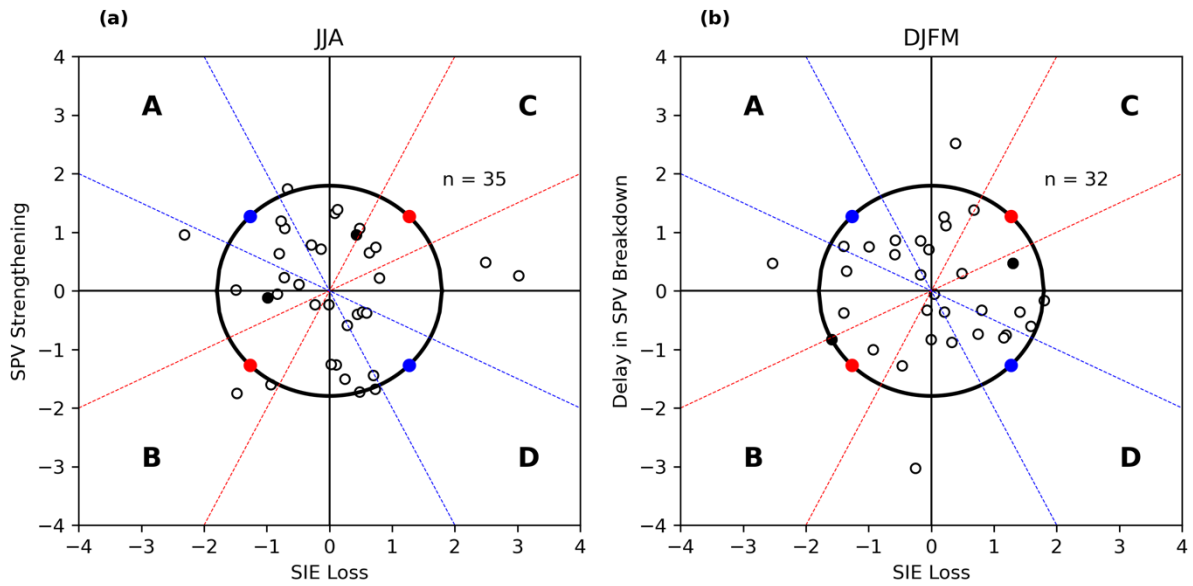


Fig. S1 Distribution of the normalised model responses for each remote driver (x-axis: SIE loss and y-axis: SPV strengthening, expressed as σ from the MME response) for **a** winter and **b** summer. The black solid lines correspond to the multimodel mean change for each respective driver and the joint fitted 80% confidence ellipse of the χ^2 distribution (with two degrees of freedom). Storylines B and C are shown as red dots on the ellipse with Storylines A and D as blue dots. Candidate models most representative of each storyline reside within the two dotted lines in each quadrant. The actual chosen models for Storylines B and C are shown in black (modified from Fig. 5 of Williams et al. 2024)

S2 Choice of storyline models

This section provides a summary of how the CMIP6 models were chosen to represent a storyline: full details can be found in Williams et al. (2024). As it is known that the skill of CMIP6 models to reproduce Antarctic climate varies markedly (Tewari et al. 2022), as a first selection stage, a scoring metric was employed to determine the best of the 41 CMIP6 models examined (see Table 1 of Williams et al. 2024). First, for each season, all outlying models were removed — defined as those having one or more months with a value of SIE or U50 more than two standard deviations from the MME based on the present period (1985-2014). In addition, models were also omitted if the integrated ice edge error (IIEE) exceeded 80% of the total SIE in any given month. The IIEE is a metric that quantifies both the cumulative error in sea ice edge location and the absolute error in SIE with respect to a reference (Goessling et al. 2016), in this case the ERA5 reanalysis (Hersbach et al. 2020). The removal of outliers reduced the number of models in winter and summer to 35 and 32, respectively (see Fig. S1).

Subsequently, these models were further scored by comparing the two storyline predictors and two additional key variables against ERA5 across the present period for each season:

1. U50 (50°–60°S): November/December (ND) and JJA
2. SH SIE: DJFM and JJA
3. SAT (50°–90°S): DJFM and JJA
4. U850 (40°–70°S): DJFM and JJA

The additional variables are useful in assessing the SAM-SAT relationship: SAT itself needs to be accurately reproduced while U850 relates to the mid latitude jet characteristics, which impact the SAM. For the three atmospheric variables, an area-weighted root-mean-square error (RMSE) and a normalised interannual variance metric (σ_{Norm}^2) were used as validation statistics, defined in Eqs. (S4) and (S5):

$$\text{RMSE} = \sqrt{\sum_{x=1}^m w_x (\text{MOD}_x - \text{ERA}_x)^2} \quad (\text{S4})$$

$$\sigma_{\text{Norm}}^2 = \sum_{x=1}^m w_x \left(\frac{\sigma_{\text{MOD}}^2 - \sigma_{\text{ERA}}^2}{\sigma_{\text{ERA}}^2} \right) \quad (\text{S5})$$

where MOD and ERA refer to a model and ERA5, respectively. The RMSE was calculated as the square root of the total of the area-weighted (w_x) sum of the squared difference between a model and ERA5 for each variable across m models with x grid points for 1985-2014 as a whole (Eq. (S4)). Similarly, σ_{Norm}^2 was calculated from Eq. (S5) using the individual years in the present period to compute the variances from the models and ERA5. For SIE, the IIEE was utilised rather than RMSE and is defined such that it already has the spatial aspect accounted for. Variance was calculated over all 30 years for the normalised IIEE (Eq. (S6)):

$$\text{IIEE}_{\text{Norm}} = \left(\frac{\text{IIEE}_{\text{MOD}} - \text{SIE}_{\text{ERA}}}{\text{SIE}_{\text{ERA}}} \right) \times (-1) \quad (\text{S6})$$

where IIEE_{MOD} is the IIEE calculated for each model and SIE_{ERA} is the SIE calculated from ERA5. Multiplication by -1 ensures that a perfect model would have an IIEE of 1 whilst an IIEE the same as the ERA5 SIE equates to 0.

A mean (x) and standard deviation (σ) was computed across all models for both tests for the four variables, thus giving a total of eight tests. For a model to ‘pass’ a test it had to lie within the range of $x \pm \sigma$. The majority of models — approximately two-thirds — had a score of 7 or 8 so those with 7 were subdivided into those that failed a test pertaining to one of the predictor variables (7) and those that failed a nonpredictor test (7*).

An ideal candidate model was one that had a score of 8 while being highly representative of a storyline (lying within the pair of dotted lines in Fig. S1). Fig. S1a demonstrates that this was not possible for Storylines B and C in winter so compromises had to be made: both chosen models — CAMS-CSM1-0 and MPI-ESM1-2_LR for Storylines B and C, respectively — had a score of 7* and were within the correct quadrant but not highly representative of their respective storylines. In summer, the two chosen models — CESM2-WACCM and MPI-ESM1-2-LR for Storylines B and C, respectively — both had scores of 8 and the former model lay within the ideal storyline position while the latter lay just outside (Fig. S1b).

Table S1 Location and data availability for the present period (1985-2014) of the 17 Antarctic meteorological stations used in this study

	Location		Data availability (%)	
	Latitude (°S)	Longitude (°E)	Winter	Summer
Amundsen-Scott	90.0	0.0	100.0	100.0
Novolazarevskaya	70.8	11.8	100.0	100.0
Syowa	69.0	39.6	100.0	100.0
Mawson	67.6	62.9	100.0	100.0
Davis	68.6	78.0	100.0	100.0
Mirny	66.6	93.0	100.0	100.0
Vostok	78.4	106.9	90.0	82.8
Casey	66.3	110.5	100.0	100.0
Dumont 'D'Urville	66.7	140.0	100.0	100.0
McMurdo	77.8	166.7	86.7	75.9
Byrd	80.0	240.6	100.0	100.0
Rothera	67.6	291.9	96.7	100.0
Vernadsky	65.2	295.7	100.0	100.0
Bellingshausen	62.2	301.0	100.0	100.0
Esperanza	63.4	303.0	100.0	100.0
Orcadas	60.8	315.3	96.7	96.6
Neumayer	70.6	351.8	100.0	96.6

Table S2 Zonal wave-number parameters within the SAM structure in the storyline models and ERA5 for the present period (1985-2014). Asterisks in the Storyline B data indicate a significant difference between the two storylines: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

	Amplitude	Phase (°E)	Explained variance (%)
Storyline B			
Wave 1	0.05	69	8.2
Wave 2	0.11	25	40.0
Wave 3	0.05*	63	8.2
Wave 4	0.10	9	30.6
Storyline C			
Wave 1	0.26	88	40.8
Wave 2	0.25	1	37.9
Wave 3	0.16	10	15.9
Wave 4	0.08	17	3.7
ERA5			
Wave 1	0.15	102	17.0
Wave 2	0.20	165	31.9
Wave 3	0.22	83	39.3
Wave 4	0.07	34	4.0

Table S3 As Table S2 for the future period (2071-2099)

	Amplitude	Phase (°E)	Explained variance (%)
Storyline B			
Wave 1	0.07	200	4.6
Wave 2	0.20	163	36.5
Wave 3	0.22	79	48.3
Wave 4	0.08	29	6.2
Storyline C			
Wave 1	0.11	240	8.6
Wave 2	0.27	158	49.9
Wave 3	0.22	87	33.7
Wave 4	0.07	75	3.1

Table S4 As Table S2 for summer

	Amplitude	Phase (°E)	Explained variance (%)
Storyline B			
Wave 1	0.22	319	75.9
Wave 2	0.08	90	10.9*
Wave 3	0.08	42	9.0
Wave 4	0.02	13	0.7
Storyline C			
Wave 1	0.32	50	58.3
Wave 2	0.16	147	14.8
Wave 3	0.19	48	20.3
Wave 4	0.09	73	4.7
ERA5			
Wave 1	0.09	47	9.2
Wave 2	0.17	151	36.9
Wave 3	0.08	61	7.2
Wave 4	0.19	6	45.8

Table S5 As Table S4 for the future period (2071-2099)

	Amplitude	Phase (°E)	Explained variance (%)
Storyline B			
Wave 1	0.07	246	19.6
Wave 2	0.07	18*	19.7
Wave 3	0.09	1	29.2
Wave 4	0.07	61	22.2
Storyline C			
Wave 1	0.12	133	30.5
Wave 2	0.13	158	33.5
Wave 3	0.11	97	25.5
Wave 4	0.04	39	3.1

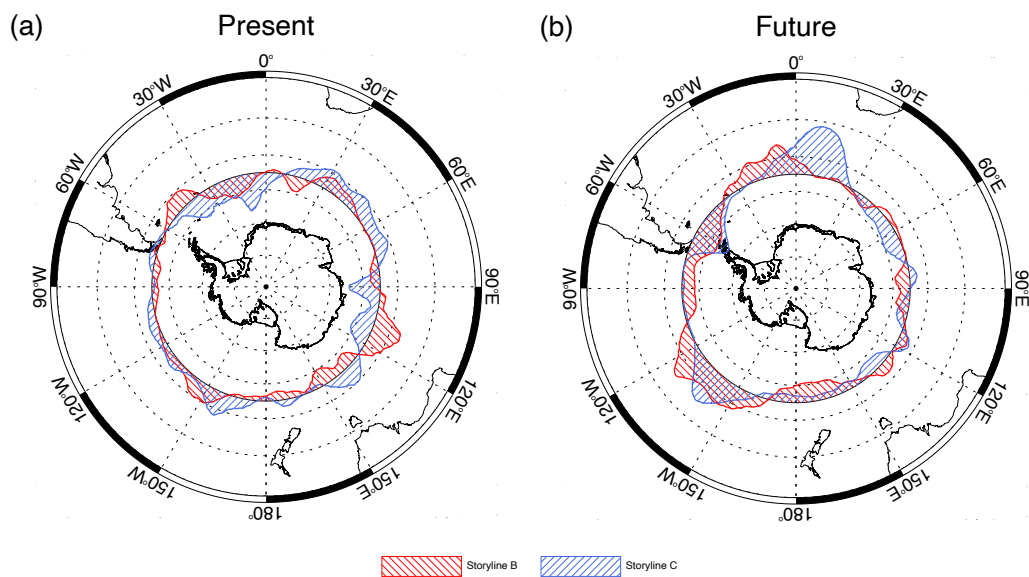


Fig. S2 Longitudinal variability in the strength of the winter meridional wind component associated with SAM+ during **a** the present (1985-2014) and **b** the future (2070-2099) periods. Storyline B is shown in red and Storyline C in blue. The relative magnitude of the northerly (southerly) winds are plotted proportionately south (north) of 55°S

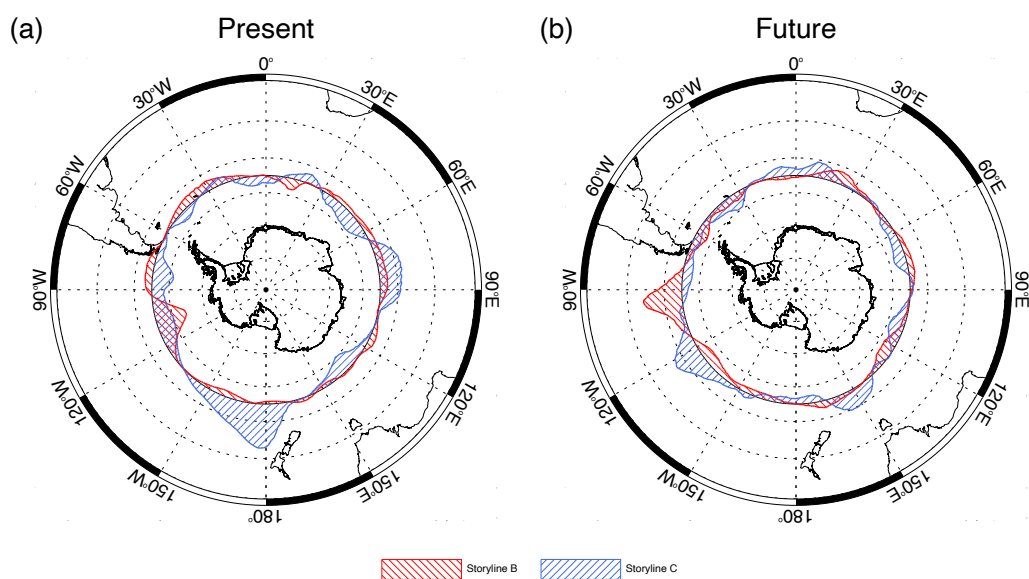


Fig. S3 As Fig. S2 for summer

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