

Amplifying Variability of the Southern Annular Mode in the Past and Future

Ding Ma^{1, 2}, Yuandong Zhang¹, and Ji Nie^{3,4,5*}

1. Division of Natural and Applied Sciences, Duke Kunshan University, Kunshan, Jiangsu, China
2. Environmental Research Center, Duke Kunshan University, Kunshan, Jiangsu, China
3. Laboratory for Climate and Ocean-Atmosphere Studies, Department of Atmospheric and Oceanic Sciences, School of Physics, Peking University, Beijing, China
4. China Meteorological Administration Tornado Key Laboratory, Foshan, China
5. Institute of Carbon Neutrality, Peking University, Beijing, China

Corresponding author address: Ji Nie, Email: jnie@pku.edu.cn

Abstract

The Southern Annular Mode (SAM) is the dominant mode of atmospheric variability in the Southern Hemisphere extratropics. While its long-term positive trend is well-documented, changes in the amplitude of SAM variability remain poorly understood. Based on reanalysis data and surface-station observations, we demonstrate that SAM variability has substantially increased over the past eight decades, coinciding with more frequent and severe weather extremes. A simple model and idealized climate experiments reveal that this amplification is primarily driven by enhanced eddy momentum flux, which is mechanistically linked to a strengthened meridional temperature gradient. State-of-the-art climate model projections under high-emission scenarios indicate that SAM variability will likely continue to intensify throughout the 21st century, driven by a further increase in the meridional temperature gradient. These findings highlight a critical but previously overlooked response of large-scale circulation to climate change, with important implications for assessing and mitigating future climate risks across the Southern Hemisphere.

17

Significance

18 The Southern Annular Mode (SAM) is a major driver of weather variability across
19 the Southern Hemisphere extratropics. How the SAM variability will change in the
20 future has significant implications for weather and its impacts: more extremely
21 abnormal SAM event is associated with stronger weather extremes. Here, we
22 demonstrate that SAM variability, along with its associated weather extremes, has
23 significantly intensified over the past eight decades and will continue to amplify under
24 future warming. The mechanism of the amplification as enhanced atmospheric eddy
25 activity driven by a strengthening equator-to-pole temperature gradient. Our findings
26 reveal that increasing SAM variability represents a critical but underappreciated
27 dimension of climate change, with major implications for understanding and predicting
28 future weather extremes in the Southern Hemisphere.

29

30 **1. Introduction**

31 The Southern Annular Mode (SAM), defined by a dipole of atmospheric pressure
32 anomalies between the mid- and high latitudes of the Southern Hemisphere (SH),
33 represents the leading mode of large-scale atmospheric variability in the SH
34 extratropics (Thompson and Wallace, 2000; Gong and Wang, 1999). Positive (negative)
35 phases of SAM are associated with a poleward (equatorward) shift of the westerly jet
36 (Lorenz and Hartmann, 2001). SAM exerts a profound influence on SH climate and
37 weather, modulating temperature, precipitation, storm activity, and sea ice extent
38 (Gillett et al., 2006; Pezza et al., 2008; Doddridge and Marshall, 2017; Holz et al., 2017).
39 In addition, SAM affects Southern Ocean circulation, biogeochemistry, and carbon
40 uptake (Lovenduski et al., 2007), highlighting its important role in the Earth system. A
41 comprehensive understanding of SAM is therefore critical for interpreting past climate
42 variability and improving projections of future climate change.

43 Previous studies have consistently documented a robust trend toward the positive
44 phase of the SAM in recent decades (Thompson et al., 2000; Kushner et al., 2001;
45 Marshall, 2003). This shift has been primarily attributed to stratospheric ozone
46 depletion (Thompson et al., 2011). Concurrently, rising greenhouse gas concentrations
47 intensify tropical tropospheric warming and enhance the meridional temperature
48 gradient. This greenhouse-driven effect is expected to sustain the positive SAM trend
49 even as stratospheric ozone recovers in the coming decades (Arblaster and Meehl, 2006;
50 Arblaster et al., 2011). Consistent with these mechanisms, climate simulations from the
51 Coupled Model Intercomparison Project Phase 6 (CMIP6) project a continued shift to

52 the positive SAM phase through the end of the 21st century (Goyal et al., 2021).

53 However, little research has focused on changes in the variability of the SAM,

54 which may be equally important as shifts in its mean state for regional weather and

55 climate. While a change in the mean SAM state implies a systematic shift in

56 atmospheric circulation—such as displacement of the jet—that can alter weather

57 patterns (Gillett et al., 2006; Pezza et al., 2008), an increase in SAM variability implies

58 more frequent or extreme deviations from the mean, thereby elevating the likelihood of

59 weather extremes. Importantly, similar distinctions between mean and variability

60 responses have been identified in other climate phenomena. For example, the sensitivity

61 of extreme precipitation to global warming is substantially greater than that of mean

62 precipitation (e.g., Seneviratne et al., 2021; Nie et al., 2020). Likewise, the El Niño–

63 Southern Oscillation (ENSO) is projected to exhibit increased variability under climate

64 warming, even though there is no consensus on its mean state changes (Cai et al., 2022;

65 Lee et al., 2022). These examples underscore the critical need to understand not only

66 the mean state response of the SAM, but also potential changes in its variability.

67 This study quantifies historical and projected changes in SAM variability and

68 investigates the underlying mechanisms. We: (1) present observational evidence for a

69 significant increase in daily SAM variability since the 1940s, accompanied by a

70 corresponding intensification of associated weather extremes; (2) identify the primary

71 drivers of this variability amplification using a simple theoretical model and idealized

72 climate model simulations; and (3) demonstrate that SAM variability is likely to

73 continue increasing under anthropogenic forcing through the end of the 21st century.

74 These findings underscore that enhanced SAM variability constitutes a critical, yet
75 previously underappreciated, facet of the SH climate response to global change, with
76 important implications for future weather extremes and climate risk assessment.

77

78 **2. Results**

79 **2.1 Historical Amplification of SAM Variability**

80 The historical amplification of SAM variability is clearly evident in the evolving
81 probability distribution of the daily SAM index (z ; see Methods), derived from the fifth-
82 generation ECMWF reanalysis (ERA5) beginning in 1940 (Figure 1a). Comparing the
83 periods 1940–1979 and 1980–2019, the distribution shifts toward more positive values,
84 consistent with the well-documented mean-state trend toward a positive SAM phase
85 (e.g., Thompson et al., 2011). Notably, we emphasize the change in the distribution’s
86 width—quantified by ± 2 standard deviations (vertical dashed lines in Figure 1a)—
87 which expands substantially over time. This widening even dominates the mean shift
88 in its impact on extreme negative SAM events, which become more frequent and
89 intense during the later period despite the overall positive trend. The increase in SAM
90 variability is further confirmed by the year-to-year standard deviation of the daily SAM
91 index (σ_z ; Figure 1b), which rises significantly from a mean of 9.61 in 1940–1979 to
92 10.96 in 1980–2019, representing a 14% increase. Comparable trends are observed in
93 other reanalysis datasets, such as the NCEP reanalysis (Figure S1), supporting the
94 robustness of these findings.

95 The observed amplification of SAM variability translates directly into more

96 pronounced weather extremes. To illustrate these impacts, we composite anomalies of
97 precipitation, zonal wind, and temperature associated with daily SAM events exceeding
98 ± 1 standard deviation (see Methods). Figure 2a presents precipitation anomaly
99 composites averaged over 20°S–40°S—a latitude band selected for consistency with
100 Australian surface observations (Figure S2)—during strong positive SAM events, with
101 longitudes shifted to align regional structures (see Methods). The composites reveal a
102 wave-like precipitation pattern characteristic of synoptic-scale disturbances, with
103 anomaly peaks positioned slightly downstream of the center. Notably, the amplitude of
104 the peak positive precipitation anomaly increases by approximately 0.6 mm day⁻¹
105 between the earlier (1940–1979) and later (1980–2019) periods, corresponding to a 40%
106 fractional increase. These reanalysis-based results are corroborated by Australian
107 surface-station precipitation data (Figure 2b), which exhibit comparable enhancements
108 in precipitation anomalies during positive SAM events.

109 Further insights into the precipitation patterns are provided by the latitude–
110 longitude composites of SAM-related anomalies (Figure S3). During positive SAM
111 events, strong negative precipitation anomalies are centered around 45°S (absolute
112 latitude) and 0° (relative longitude), flanked by positive anomalies along a northeast–
113 southwest orientation (Figure S3a). In the later period, there is an enhancement of the
114 downstream positive precipitation anomaly (Figure S3b), consistent with the zonal
115 average map (Figure 2). In contrast, negative SAM events are characterized by positive
116 precipitation anomalies located slightly downstream of the composite center (Figure
117 S3c). In the later period, the positive anomalies are more spatially confined and centered

118 around 45°S (Figure S3d). There are negligible changes in the zonally averaged (20°S–
119 40°S) precipitation anomalies between the two periods, as confirmed by both reanalysis
120 and surface data (Figure S4). It is noteworthy that the regional structure and phase
121 asymmetric precipitation response between positive and negative SAM events are
122 consistent with previous studies emphasizing the zonal structure of SAM and its
123 interaction with atmospheric waves (Kushner and Lee, 2007; Luo et al., 2007; Luo et
124 al., 2018).

125 The amplified variability of the SAM is also evident in other key meteorological
126 variables, including zonal wind and temperature. Composites of vertically averaged
127 zonal wind anomalies during strong SAM events exhibit local meridional dipole
128 patterns (Figures S5a, c), which become more pronounced in the later period due to the
129 increased SAM variability (Figures S5b, d). Similarly, composites of lower-
130 tropospheric temperature anomalies show stronger temperature fluctuations in the later
131 period (Figure S6). In these composites, the long-term trends are removed to isolate the
132 anomalies associated with SAM variability. These results indicate that the amplified
133 SAM variability contributes to substantial and spatially coherent changes in regional
134 wind and temperature patterns, underscoring its broader implications for extreme
135 weather events in the SH.

136

137 **2.2 Driver of the SAM Variability Amplification**

138 To investigate the dynamical processes underlying the observed amplification of
139 SAM variability, we employ a simple, theoretical model that captures the essential

140 interaction between the SAM and eddy momentum forcing (Lorenz and Hartmann,
141 2001; see Methods). This model estimates SAM variability given the input of stochastic
142 eddy momentum forcing (\tilde{m}), with parameterized eddy–jet feedback (by a strength
143 parameter b) and damping (by damping timescale τ). Here, we use this model as a
144 diagnostic tool to understand the mechanisms driving changes in SAM variability over
145 time.

146 We begin by validating the simple model. Using the diagnosed parameters and
147 stochastic eddy momentum forcing from reanalysis, the model reproduces the year-to-
148 year SAM variability (σ_z) with good fidelity (Figure S8a). Notably, both the model
149 parameters (Table S1) and the eddy momentum forcing (\tilde{m} ; Figure S7a) differ between
150 the early and later periods. These differences suggest that the observed changes in SAM
151 variability may result from variations in both the parameterized processes and the
152 external forcing. To disentangle their respective contributions, we first recompute σ_z
153 using the same parameter values (b and τ) for both periods. The results still exhibit a
154 substantial increase in σ_z after 1979 (Figure S8b). In contrast, when we adjust \tilde{m}
155 such that its mean is held constant across the two periods (Figure S7b), the amplification
156 in σ_z largely disappears (Figure S8c). These calculations indicate that the increase in
157 SAM variability is primarily driven by enhanced variability in the eddy momentum
158 forcing, rather than by changes in the eddy–jet feedback or damping.

159 What, then, drives the increase in the variability of eddy momentum forcing? We
160 propose that this enhanced variability arises from a strengthened meridional
161 temperature gradient. As shown in Figure 3a, the 250-hPa temperature difference

162 between 20°S and 70°S—a proxy for the mid-latitude meridional temperature
163 gradient—increases by approximately 1 K from the 1940–1979 period to 1980–2019.
164 Statistical analyses support the following causal pathway: a stronger meridional
165 temperature gradient enhances eddy activity, reflected in increased eddy momentum
166 flux (O’Gorman 2010; Figure S9a), which is associated with greater variability in eddy
167 momentum flux (Figure S9b). This, in turn, drives amplified SAM variability (Figure
168 S9c), as suggested by the simple model. Collectively, these results highlight a positive
169 linkage between the meridional temperature gradient and SAM variability (Figure 3a),
170 providing a physically consistent explanation for the observed amplification.

171 To further evaluate the proposed mechanism, we conduct a series of idealized
172 experiments using the Geophysical Fluid Dynamics Laboratory (GFDL) dry dynamical
173 core model (Methods). This model excludes moist processes and topographic
174 influences, enabling a focused examination of eddy–mean flow interactions. We
175 systematically vary the prescribed equilibrium meridional temperature gradient across
176 simulations. The results reveal a clear and robust relationship: a stronger meridional
177 temperature gradient leads to increased SAM variability (Figure 3b). The ability of
178 these idealized simulations to reproduce the key features in observations provides
179 strong support for our proposed mechanism, linking the amplification of SAM
180 variability to background climate changes associated with global warming.

181

182 **2.3 Continuous Increase of SAM Variability in the Future**

183 Having established the historical amplification of SAM variability and its

184 underlying drivers, we now turn to its future projection. To assess how SAM variability
185 may respond to future global warming, we analyze an ensemble of climate simulations
186 from 25 CMIP6 models under the high-emissions scenario SSP5-8.5. These simulations
187 consistently project that SAM variability will continue to increase in a warming climate.
188 Comparing the future period (2060–2099) with a historical baseline (1980–2019), the
189 multi-model mean shows a clear and statistically significant increase in the amplitude
190 of SAM variability by the end of the 21st century (Figure 4). Notably, 19 out of 25
191 models project a further amplification of SAM variability, although the magnitude of
192 the projected change exhibits sizeable inter-model spread.

193 All 25 CMIP6 models project an enhancement of the meridional temperature
194 gradient in the SH (Figure 4). This feature is a robust climate response, primarily driven
195 by the delayed warming over the Southern Ocean (Simpkins, 2024). In contrast, the
196 Northern Hemisphere exhibits a weakening meridional temperature gradient due to
197 Arctic amplification (Douville, 2023), and studies suggest that the North Atlantic
198 Oscillation (NAO) may become less variable in a warming climate (Mitevski et al.,
199 2025). These opposing hemispheric responses in both the meridional temperature
200 gradient and annular mode variability are nonetheless consistent with our proposed
201 mechanism. While the majority of CMIP6 models project an increase in SAM
202 variability, six models show a slight weakening despite projecting a stronger meridional
203 temperature gradient. This discrepancy suggests that additional factors may also
204 influence SAM variability in these cases. Possible contributors include changes in the
205 characteristic wavelength of eddies, which can modulate the eddy–jet feedback strength

206 (Kidston et al., 2010; Dai and Nie, 2020), and biases in the models' climatological states
207 that affect baroclinic instability and eddy dynamics (Chemke et al., 2022).

208

209 **3. Conclusions and Discussion**

210 This study presents comprehensive evidence for a significant amplification of
211 SAM variability over the past eight decades —an impactful shift in the behavior of the
212 dominant mode of atmospheric variability in the SH extratropics. The enhanced
213 variability is associated with intensified weather anomalies linked to SAM, as
214 confirmed by both reanalysis and surface-station observations. Using a theoretical
215 model and idealized simulations, we identify the primary driver of this amplification as
216 strengthened meridional temperature gradient. Climate projections from CMIP6
217 models suggest that this amplification of SAM variability is likely to continue through
218 the end of the 21st century under global warming, consistent with the projected
219 intensification of the SH meridional temperature gradient.

220 Our findings have important implications for future changes in the extreme
221 weather in the SH. The combined effect of a projected increase in SAM variability and
222 a continued positive trend in its mean state is expected to result in more frequent and
223 intense extreme positive SAM events (as illustrated in Figure 1a), along with their
224 associated weather extremes. Moreover, our results reveal phase asymmetry in SAM-
225 associated weather anomalies and their response to variability changes. This is
226 consistent with prior studies that have identified inherent phase asymmetry in the
227 dynamics of annular modes (Luo et al., 2007; Mitevski et al., 2025). This study focuses

228 on projections through the end of the 21st century. Over the time-scale of hundreds of
229 years, as South Ocean warming eventually catches up with the global mean (e.g.,
230 Coulon et al. 2024), the SH circulation and SAM behavior may undergo abrupt
231 transitions. Finally, our findings underscore the importance of moving beyond mean-
232 state analysis when evaluating future climate. Variability in large-scale atmospheric
233 modes such as the SAM plays a critical role in shaping regional climate extremes. A
234 comprehensive understanding of both mean and variability changes is essential to
235 provide more interpretable climate projections for policymakers and stakeholders.

236

237

238 **Methods**

239 **Data.** We quantify historical changes in SAM variability from 1940 to 2019 using the
240 fifth-generation European Centre for Medium-Range Weather Forecasts (ECMWF)
241 reanalysis (ERA5; Hersbach et al., 2020). The analysis employs four-times-daily ERA5
242 data at a horizontal resolution of $1^\circ \times 1^\circ$. We also utilize the National Centers for
243 Environmental Prediction (NCEP) reanalysis (Kalnay et al., 1996), available at a
244 resolution of 2.5° , spanning 1948–2019. To provide independent observational support,
245 we examine daily in situ measurements from 1,995 Australian surface weather stations
246 (Jones et al., 2009). The stations mostly locate between 20°S and 40°S (Figure S2),
247 aligning with the latitude band used in our composite analyses (Figure 2). Future
248 climate projections are based on daily output from 25 CMIP6 models (Eyring et al.,
249 2016). The high-emission SSP5-8.5 scenario is examined here. In analysis, we remove

250 the climatological seasonal cycle, defined as the annual mean plus the first four Fourier
251 harmonics of the daily climatology, from all datasets. All meteorological fields are
252 subsequently linearly detrended prior to compositing to focus on variability rather than
253 long-term trends.

254

255 **Definition of the SAM Index.** Following established methodologies (e.g., Lorenz and
256 Hartmann, 2001), the SAM index is defined as the principal component time series
257 associated with the leading empirical orthogonal function (EOF) of SH zonal-mean
258 zonal wind anomalies. This definition is applied consistently across all datasets,
259 including reanalysis products, idealized model simulations, and CMIP6 outputs.

260

261 **Composites.** Strong positive and negative SAM events are identified as days when the
262 daily SAM index exceeds ± 1 standard deviation. The standard deviation thresholds are
263 calculated separately for the earlier (1940–1979) and later (1980–2019) periods.
264 Composites of precipitation, temperature, and zonal wind anomalies are then
265 constructed based on these anomalous SAM events. Although the SAM is defined as a
266 zonally symmetric mode, the associated weather anomalies often exhibit zonally
267 localized patterns. To identify and align these regional features in the composites, we
268 adopt the local dipole index introduced by Kushner and Lee (2007). This index
269 quantifies longitudinal variations in the jet stream by projecting zonal wind anomalies
270 at each longitude onto the meridional dipole pattern defined by the SAM. When
271 constructing composite maps (e.g., Figures 2, S3), meteorological fields of each event

272 are longitudinally shifted such that 0° relative longitude corresponds to the longitude
273 of the maximum (for positive SAM events) or minimum (for negative SAM events) of
274 the local dipole index. The x-axes in the corresponding composite plots thus represent
275 this shifted (relative) longitude, allowing for consistent alignment of synoptic-scale
276 features across events.

277

278 **Simple Model.** To understand the dynamics underlying the observed increase in SAM
279 variability, we adopt a simple model (Lorenz and Hartmann, 2001), which is written as

280
$$\frac{dz}{dt} = m - \frac{z}{\tau}, \quad (1)$$

281 where z is the SAM index, m is the total eddy momentum forcing, and τ the
282 damping timescale. Equation 1 is the governing equation of zonal momentum (i.e., the
283 SAM index) under the eddy momentum forcing and damping. The eddy momentum
284 forcing is written as

285
$$m = \tilde{m} + bz, \quad (2)$$

286 where \tilde{m} is the stochastic eddy momentum forcing that is externally specified as
287 inputs of the model. bz represents the eddy-jet feedback, with feedback strength of b .
288 The parameters τ and b are treated as constants, at least for a certain time period. The
289 input, \tilde{m} , allows annual variability. Here we use the simple model as a tool to
290 understand the changes in SAM variability. Thus, the parameters (τ and b) and model
291 input (\tilde{m}) are not prescribed a priori, but diagnosed from the reanalysis following the
292 method in Lorenz and Hartmann (2001). With diagnosed b , τ (Table S1), and \tilde{m}
293 (Figure S7a), the simple model can reproduce the observed SAM variability very well

294 (Figure S8a), indicating its capability in explaining the changes in SAM variability.

295

296 **Idealized Climate Experiments.** Numerical experiments were conducted using the
297 Geophysical Fluid Dynamics Laboratory (GFDL) dry dynamical core model. This
298 idealized model excludes moisture processes and represents surface conditions using a
299 homogeneous lower boundary with no topography. Radiation is simplified as a
300 relaxation of atmospheric temperature toward a prescribed, zonally symmetric radiative
301 equilibrium temperature profile, with equator-to-pole surface temperature difference
302 (ΔT_y ; Held and Suarez, 1994). This modeling configuration has been widely used to
303 investigate eddy–jet feedbacks and annular mode dynamics (e.g., Ma et al., 2017). To
304 explore the link between meridional temperature gradients and SAM variability, we
305 perform a suite of simulations in which ΔT_y is systematically varied from 45 K to 70
306 K in 5 K increments. Each simulation is integrated for 15,600 model days at T63
307 horizontal resolution (approximately 200 km grid spacing), with 40 vertical levels and
308 6-hourly output. The initial 1,000 days are discarded as spin-up, and the remaining 40
309 years of data are used for analysis. Owing to the model’s hemispheric symmetry, each
310 simulation effectively provides 80 years of annular mode data.

311

312

313 **Acknowledgments**

314 This work is supported by Jiangsu Natural Science Foundation Grant BK20241828
315 (to D.M.), National Key R&D Program of China grant 2023YFF0805200 and National

316 Natural Science Foundation of China 42375057 (to J.N.).

317

318 **Author contributions**

319 D.M. and J.N. designed and performed the study. D.M. and Y.Z. conducted data
320 analysis. D.M. and J.N. wrote the paper with contributions from Y.Z.

321

322 **Competing interests**

323 The authors declare no competing interests.

324

325 **Materials & Correspondence**

326 Correspondence and requests for materials should be addressed to J.N.

327

328 **Data availability**

329 The ERA5 reanalysis is available at
330 <https://cds.climate.copernicus.eu/datasets/reanalysis-era5-pressure-levels>. The surface-
331 station observational data are provided by the Australian Bureau of Meteorology at
332 <http://www.bom.gov.au/climate/data/>. The CMIP6 climate simulation dataset is
333 available at <https://esgf-node.llnl.gov/search/cmip6/>. The analyses data in the paper will
334 be made available after the first round of review.

335

336 **References**

- 337 Arblaster J, Meehl G (2006) Contributions of External Forcings to Southern Annular
338 Mode Trends. *Journal of Climate* 19:2896–2905.
- 339 Arblaster J, Meehl G, Karoly D (2011) Future Climate Change in the Southern
340 Hemisphere: Competing Effects of Ozone and Greenhouse Gases. *Geophysical
341 Research Letters* 38(2):L02701.
- 342 Cai, W, et al. (2022) Increased ENSO Sea Surface Temperature Variability Under
343 Four IPCC Emission Scenarios. *Nature Climate Change* 12:228–231.
- 344 Chemke R, Ming Y, Yuval J (2022) The Intensification of Winter Mid-Latitude Storm
345 Tracks in the Southern Hemisphere. *Nature Climate Change* 12(6):553–557.
- 346 Coulon, V, et al. (2024) Disentangling the Drivers of Future Antarctic Ice Loss with a
347 Historically Calibrated Ice-Sheet Model. *The Cryosphere* 18:653–681.
- 348 Dai P, Nie J (2022) Robust Expansion of Extreme Midlatitude Storms under Global
349 Warming. *Geophysical Research Letters* 49:e2022GL099007.
- 350 Doddridge E, Marshall J (2017) Modulation of the Seasonal Cycle of Antarctic Sea
351 Ice Extent related to the Southern Annular Mode. *Geophysical Research Letters*
352 44(19):9761–9768.
- 353 Douville, H (2023) Robust and Perfectible Constraints on Human-Induced Arctic
354 Amplification. *Communications Earth and Environment* 4(1):283.
- 355 Eyring V, et al. (2016) Overview of the Coupled Model Intercomparison Project
356 Phase 6 (CMIP6) Experimental Design and Organization. *Geoscientific Model
357 Development* 9(5):1937–1958.

- 358 Gillett N, Kell T, Jones P (2006) Regional Climate Impacts of the Southern Annular
359 Mode. *Geophysical Research Letters* 33(23):L23704.
- 360 Gong D, Wang S (1999) Definition of Antarctic Oscillation Index. *Geophysical*
361 *Research Letters* 26(4):459–462.
- 362 Goyal, R., et al. (2021) Historical and Projected Changes in the Southern Hemisphere
363 Surface Westerlies. *Geophysical Research Letters* 48(4):2020GL090849.
- 364 Held I, Suarez M (1994) A Proposal for the Intercomparison of the Dynamical Cores
365 of Atmospheric General Circulation Models. *Bulletin of the American*
366 *Meteorological Society* 75:1825–1830.
- 367 Hersbach H, et al. (2020) The ERA5 Global Reanalysis. *Quarterly Journal of the*
368 *Royal Meteorological Society* 146(730):1999–2049.
- 369 Holz A, et al. (2017) Southern Annular Mode Drives Multicentury Wildfire Activity in
370 Southern South America. *Proceedings of the National Academy of Sciences*
371 114(36):9552–9557.
- 372 Jones D, Wang W, Fawcett R (2009) High-quality Spatial Climate Data-Sets for
373 Australia. *Australian Meteorological and Oceanographic* 59:233–248.
- 374 Kalnay E, et al. (1996) The NCEP/NCAR 40-Year Reanalysis Project. *Bulletin of the*
375 *American Meteorological Society* 77:437–471.
- 376 Kidston J, et al. (2010) A Robust Increase in the Eddy Length Scale in the Simulation
377 of Future Climates. *Geophysical Research Letters*, 37(3):L03806.
- 378 Kushner P, Lee G (2007) Resolving the Regional Signature of the Annular Modes.
379 *Journal of Climate* 20(12):2840–2852.

- 380 Kushner P, Held I, Del Worth T (2001) Southern Hemisphere Atmospheric Circulation
381 Response to Global Warming. *Journal of Climate* 14:2238–2249.
- 382 Lee, S, et al. (2022) On the Future Zonal Contrasts of Equatorial Pacific Climate:
383 Perspectives from Observations, Simulations, and Theories. *npj Climate and*
384 *Atmospheric Science* 5(1):82.
- 385 Lorenz D, Hartmann D (2001) Eddy-Zonal Flow Feedback in the Southern
386 Hemisphere. *Journal of the Atmospheric Sciences* 58(21):3312–3327.
- 387 Lovenduski N, Gruber N, Doney S, Lima I (2007) Enhanced CO₂ Outgassing in the
388 Southern Ocean from a Positive Phase of the Southern Annular Mode. *Global*
389 *Biogeochemical Cycles* 21(2):GB2026.
- 390 Luo D, Chen X, Feldstein S (2018) Linear and Nonlinear Dynamics of North Atlantic
391 Oscillations: A New Thinking of Symmetry Breaking. *Journal of the*
392 *Atmospheric Sciences* 75(6):1955–1977.
- 393 Luo D, Lupo A, Wan H (2007) Dynamics of Eddy-Driven Low-Frequency Dipole
394 Modes. Part I: A Simple Model of North Atlantic Oscillations. *Journal of the*
395 *Atmospheric Sciences* 64:3–28.
- 396 Ma D, Hassanzadeh P, Kuang Z (2017) Quantifying the Eddy-Jet Feedback Strength
397 of the Annular Mode in an Idealized GCM and Reanalysis Data. *Journal of the*
398 *Atmospheric Sciences* 74:393–4.
- 399 Marshall G (2003) Trends in the Southern Annular Mode from Observations and
400 Reanalyses. *Journal of Climate* 16(24):4134–4143.

- 401 Mitevski, I, et al. (2025) More Positive and Less Variable North Atlantic Oscillation at
402 High CO₂ Forcing. *npj Climate and Atmospheric Science* 8:171.
- 403 Nie J, Dai P, and Sobel A (2020) Dry and Moist Dynamics Shape Regional Patterns of
404 Extreme Precipitation Sensitivity. *Proceedings of the National Academy of
405 Sciences* 117:8757-8763.
- 406 O'Gorman, P. (2010) Understanding the Varied Response of the Extratropical Storm
407 Tracks to Climate Change. *Proceedings of the National Academy of Sciences*
408 117: 19176–19180.
- 409 Pezza A, Durrant T, Simmonds I (2008) Southern Hemisphere Synoptic Behavior in
410 Extreme Phases of SAM, ENSO, Sea Ice Extent, and Southern Australia
411 Rainfall. *Journal of Climate* 21:5566–5584.
- 412 Seneviratne S, et al. (2021) Weather and Climate Extreme Events in a Changing
413 Climate. In *IPCC Climate Change 2021: The Physical Science Basis*. Cambridge
414 University Press, Cambridge, United Kingdom and New York, NY, USA, pp.
415 1513–1766.
- 416 Simpkins, G. (2024) Drivers of Southern Ocean cooling. *Nature Review Earth and*
417 *Environment* 5(1):4.
- 418 Thompson D, et al. (2011) Signatures of the Antarctic Ozone Hole in Southern
419 Hemisphere Surface Climate Change. *Nature Geoscience* 4(11):741–749.
- 420 Thompson D, Wallace J (2000) Annular Mode in the Extratropical Circulation. Part I
421 Month-to-Month Variability. *Journal of Climate* 13(5):1000–1016.

422 Thompson D, Wallace J, Hegerl G (2000) Annular Modes in the Extratropical

423 Circulation. Part II Trends. *Journal of Climate* 13(5):1018–1036

424

Figure 1a: Histogram of the Daily SAM Index

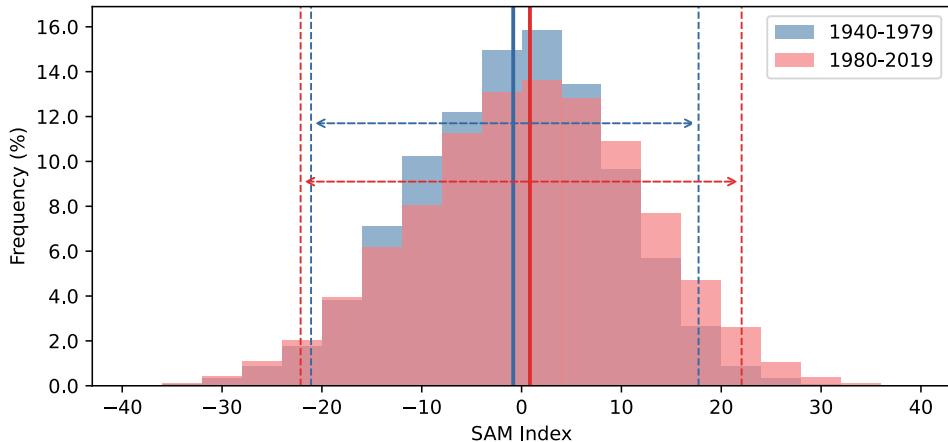
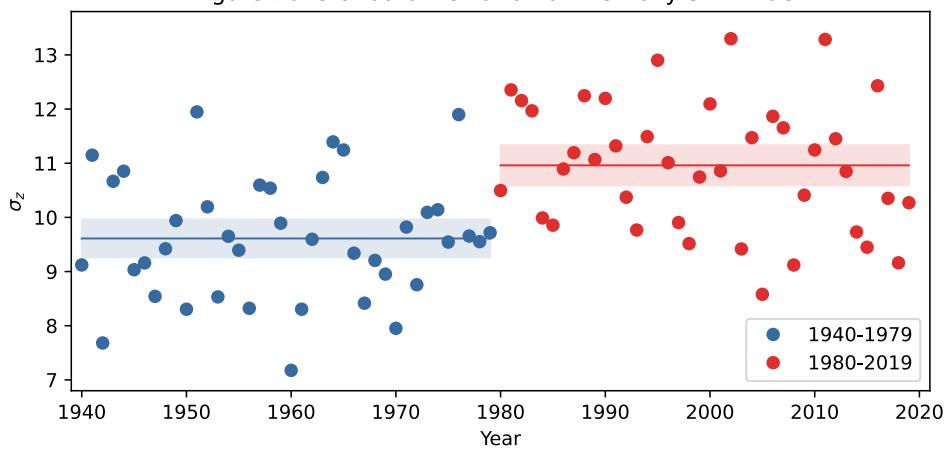


Figure 1b: Standard Deviation of the Daily SAM Index



425

426 **Figure 1. SAM variability from ERA5 data.** (a) Histograms of daily SAM index
 427 distributions for the historical periods 1940–1979 (blue) and 1980–2019 (red). Solid
 428 vertical lines indicate the period means, while dashed lines denote ± 2 standard
 429 deviations. (b) Annual standard deviation of the daily SAM index over 1940–2019.
 430 Horizontal lines show the mean values for each period, and shading represents the 95%
 431 confidence interval.

Figure 2a: Composed Precip (20° - 40° S; ERA5)

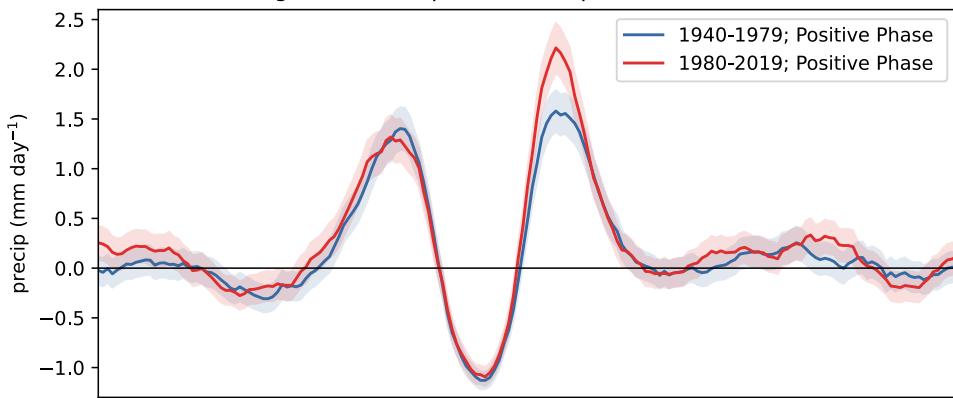
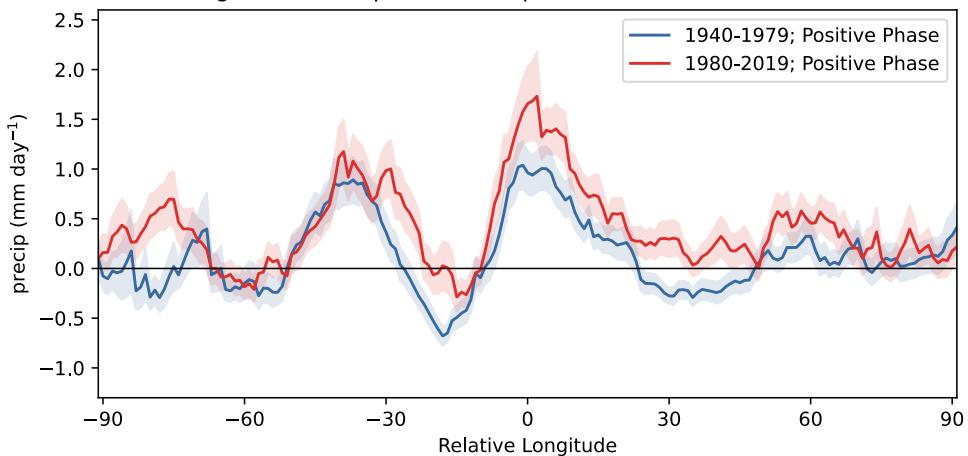


Figure 2b: Composed Precip (20° - 40° S; Surface Station)



432

433 **Figure 2. Composed precipitation anomalies (mm day⁻¹) averaged over 20° S –**

434 **40° S during strong positive SAM events. (a) ERA5 reanalysis and (b) Australian**

435 **surface station observations for the periods 1940–1979 (blue) and 1980–2019 (orange).**

436 Shading indicates the 95% confidence interval. Note that the x-axis represents relative

437 longitude, aligned to emphasize regional structures (Methods).

438

Figure 3a: ERA5 Reanalysis

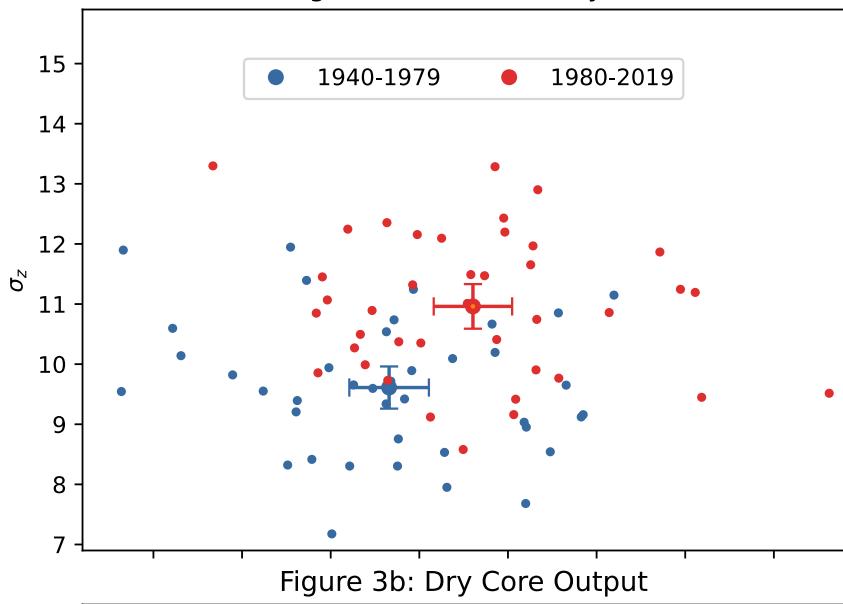
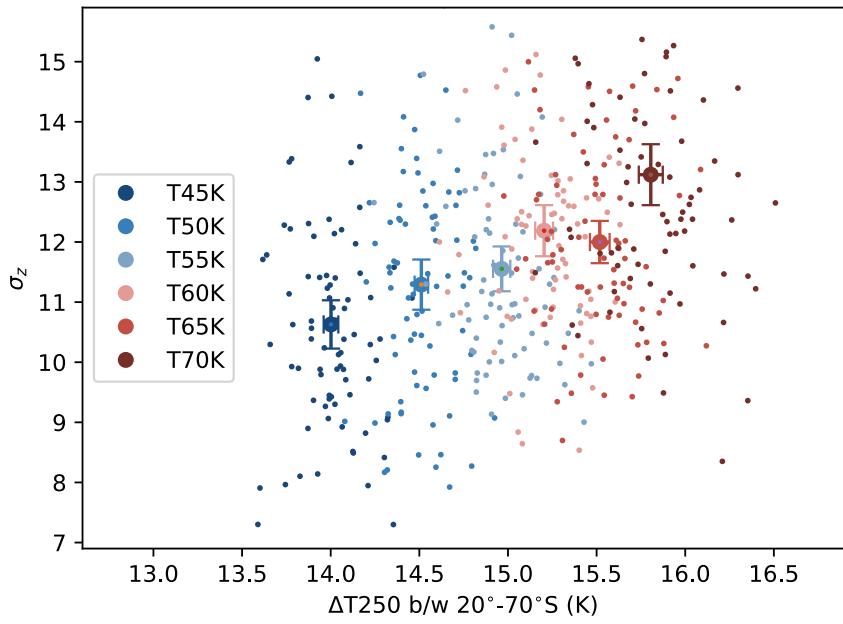
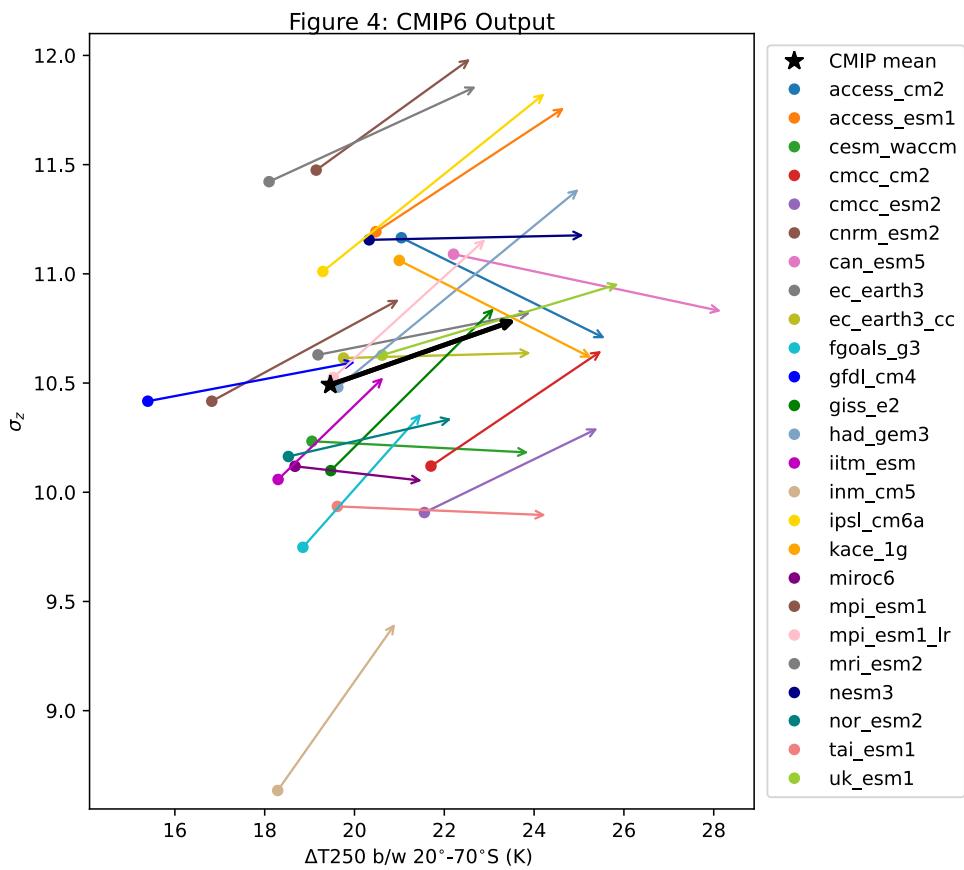


Figure 3b: Dry Core Output



439

440 **Figure 3. Relationship between SAM variability and meridional temperature**
 441 **difference.** (a) is from the ERA5 reanalysis and (b) is from the simulations using the
 442 dry dynamical core model. The x-axis is the 250-hPa temperature difference between
 443 20° S and 70° S, and the y-axis shows SAM variability. In (a), colors indicate different
 444 time period, and each dot denotes results of one year. In (b), colors indicate different
 445 experimental group, and each dot denotes results of one model year. The group means
 446 with their 95% confidence intervals are also shown.



447

448 **Figure 4. Changes in SAM variability and meridional temperature difference in**
 449 **CMIP6 simulations.** Each arrow represents an individual CMIP6 model (identified in
 450 the legend), with the starting and ending points indicating the period means for 1980–
 451 2019 and 2060–2099, respectively. The multi-model mean is shown as a bold black
 452 arrow.
 453