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Connecting the SST Pattern Problem and the Hot Model Problem

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Key Points:

- We reconcile seemingly contradicting evidences for the ability of climate models to reproduce observed surface temperature pattern trends
- All models fail to reproduce long-term trends but many also cannot simulate decadal-scale swings in the zonal equatorial Pacific
- Models with a high effective climate sensitivity reproduce decadal-scale swings much less likely

Supporting Information:

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

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Abstract In the equatorial and subtropical east Pacific Ocean, strong ocean-atmosphere coupling results in large-amplitude interannual variability. Recent literature debates whether climate models reproduce observed short and long-term surface temperature trends in this region. We reconcile the debate by reevaluating a large range of trends in initial condition ensembles of 15 climate models. We confirm that models fail to reproduce long-term trends, but also find that many models do not reproduce the observed decadal-scale swings in the East to West gradient of the equatorial Pacific. Models with high climate sensitivity are less likely to reproduce observed decadal-scale swings than models with a modest climate sensitivity, possibly due to an incorrect balance of cloud feedbacks driven by changing inversion strength versus surface warming. Our findings suggest that two not well understood problems of the current generation of climate models are connected and we highlight the need to increase understanding of decadal-scale variability.

Plain Language Summary We connect two pressing problems of current generation climate models: their inability to reproduce observed trends of surface temperatures in the equatorial Pacific Ocean and their high climate sensitivity. We first reconcile a debate on how and when models fail to reproduce the observations. We then show that models which do not reproduce short-term swings in the gradient between East and West equatorial Pacific Ocean tend to have a high climate sensitivity. Understanding this link will provide physical arguments for trusting the high climate sensitivity models more or less but requires substantial research from the ocean and atmosphere communities.

1. The Pattern Problem

The prevailing stratocumulus clouds over the equatorial and subtropical east Pacific dominate variations in the global energy budget and are highly sensitive to local and remote surface temperatures. The cause of the observed strengthening of the east-west gradient in the equatorial Pacific sea surface temperatures (SST; henceforth "gradient," Figure 1a) has been a subject of debate since the 1990s. Major questions that remain unsolved are: (a) Is the strengthening a response to greenhouse gas and/or aerosol forcing or part of decadal internal variability? and (b) Do models not capture it because of their inherent biases in the mean-state, atmosphere-ocean coupling, ocean mixing, atmospheric deep convection, cloud feedbacks, and/or inter-ocean basin interactions (e.g., Cane et al., 1997; England et al., 2014; Gregory et al., 2020; Seager et al., 2019, 2022)?

In recent years, many climate modeling centers have generated initial condition ensembles ("large ensembles," e.g., Deser et al., 2020), which greatly improve the sampling of models' internal variability. Some studies argue that the observed trends in the gradients fall within the range of trends simulated by the large ensembles (e.g., Olonscheck et al., 2020; Watanabe et al., 2021), while others argue that the observed trends lie outside the simulated range (e.g., Seager et al., 2019, 2022; Wills et al., 2022). Here, we reconcile these seemingly contradicting studies by analyzing all trends longer than 18 years between 1950 and 2020 in observations and large ensembles of 15 climate models. The ongoing debate is about the strengthening of the gradient (blue colors in Figure 1b), which is most pronounced in trends starting in the 1990s and ending in 2010s. However, recent trends starting in 1995 or later and 30-year or shorter trends centered around the 1980s indicate a weakening gradient (red colors in Figure 1b).

Coupled Model Intercomparison Project (CMIP) models do not reproduce the observed trends well (Figure 1c). We quantify the models' ability to reproduce the observed changes as $\phi = (t_{mean} - t_{obs})/\sigma$, were t_{mean} is a model's

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ensemble-mean trend and by definition its response to forced climate change, t_{obs} is the observed trend, and σ is the sample standard deviation of the particular model's large ensemble (Olonscheck & Notz, 2017, illustrated in Figure S1 of Supporting Information S1). Importantly, we do not necessarily expect the observations to lie close to the ensemble mean, since the observed value contains just one out of many possible realizations of real-world internal variability next to the unknown forced response. ϕ being larger than ± 2 states that the observations sit at the very edge or outside the distribution, implying that a model's forced response and internal variability rarely combine to match the observed gradient trend. Not only are most models unable to reproduce the long-term strengthening of the gradient (beginning in the 1950s and ending in the 2010s) but also about half of the models cannot simulate the shorter-term trends, referred to in the following as "swings" of the gradient in both directions (along the diagonal), including the weakening of the gradient around the 1980s. Similar analysis of tropical Pacific zonal wind stress and Southern Ocean SSTs also shows trend discrepancies that have been discussed in the literature (Figure S3 in Supporting Information S1; e.g., England et al., 2014; Kostov et al., 2018; Zhang et al., 2019). Depending on what period and trend-lengths the former studies sampled they tapped into these model deficiencies to varying degrees. Clear interpretations of these model deficiencies are currently missing. Notably, the recent weakening of the gradient starting in 1995 lies well within the simulated range (lower right of Figure 1a and lower left of Figure 1c).

2. The Hot Model Problem

Many models in CMIP Phase 6 have a much higher climate sensitivity than their counterparts in previous phases, and therefore their validity and applicability is being debated (e.g., Hausfather et al., 2022, and responses). The increased sensitivity stems to a large degree from a more sensitive shortwave low cloud feedback, meaning that low clouds reduce with warming, reflecting less solar radiation back to space and hence increasing global temperatures (e.g., Zelinka et al., 2020). Here, we show a potential link between the two global climate modeling problems—their inability to simulate the observed magnitude of swings of equatorial Pacific temperature trends, and their potentially erroneous climate sensitivity, by correlating the models' climate sensitivity with ϕ (Figure 2 and Figure S4 in Supporting Information S1). We use the Effective Climate Sensitivity (EffCS) calculated with an idealized simulation of 150 years following a step-forcing of quadrupling CO_2 (Gregory et al., 2004;

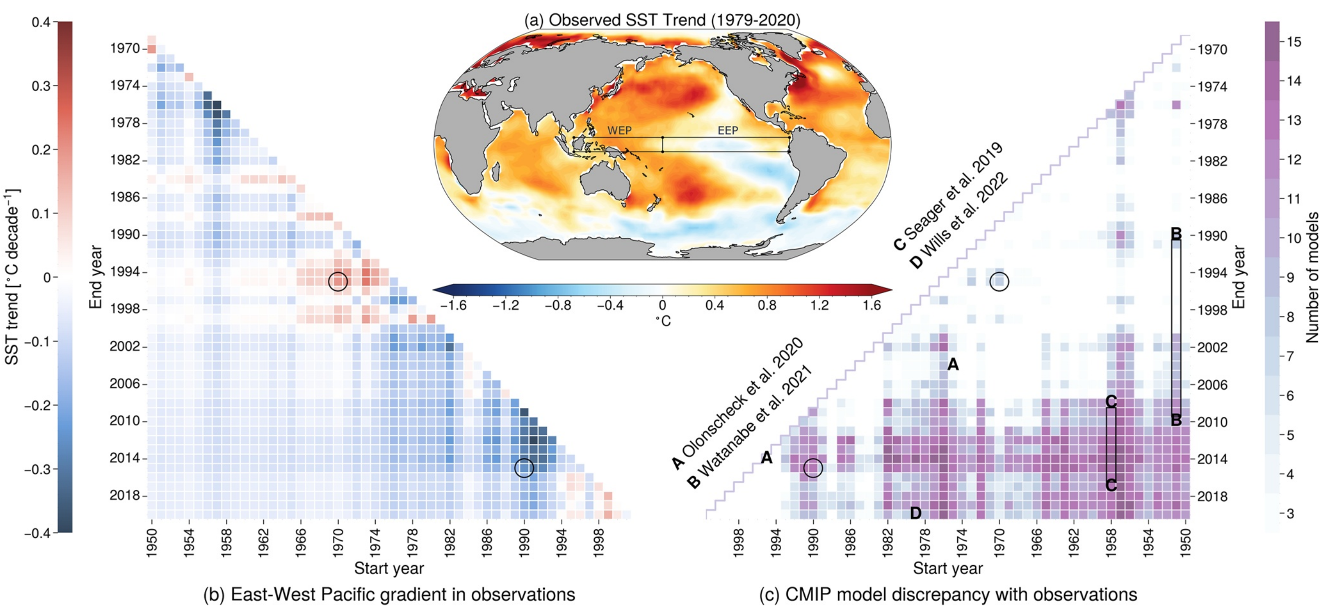

Figure 1. Surface temperature trends of various lengths in the equatorial Pacific Ocean in observations and climate model large ensembles. (a) Mean of HadISST1, ERSSTv5, and COBE 1979–2020; (b) trend differences between the Eastern Equatorial Pacific (EEP, 5°S–5°N, 180°–80°W) and Western Equatorial Pacific (WEP, 5°S–5°N, 110°E–180°; boxes indicated in panel (a) in the mean of HadISST1, ERSSTv5, and COBE for any trend longer than 18 years between 1950 and 2020; (c) Number of models for which the observations fall outside ±2 standard deviations of the model mean. See Table S1 in Supporting Information S1 for model names and number of ensemble members. Letters indicate previous studies coming to different conclusions about the discrepancy between models and observations. Circles indicate the periods shown in Figure 2. Figure S2a in Supporting Information S1 overlays panel (c) on (b).

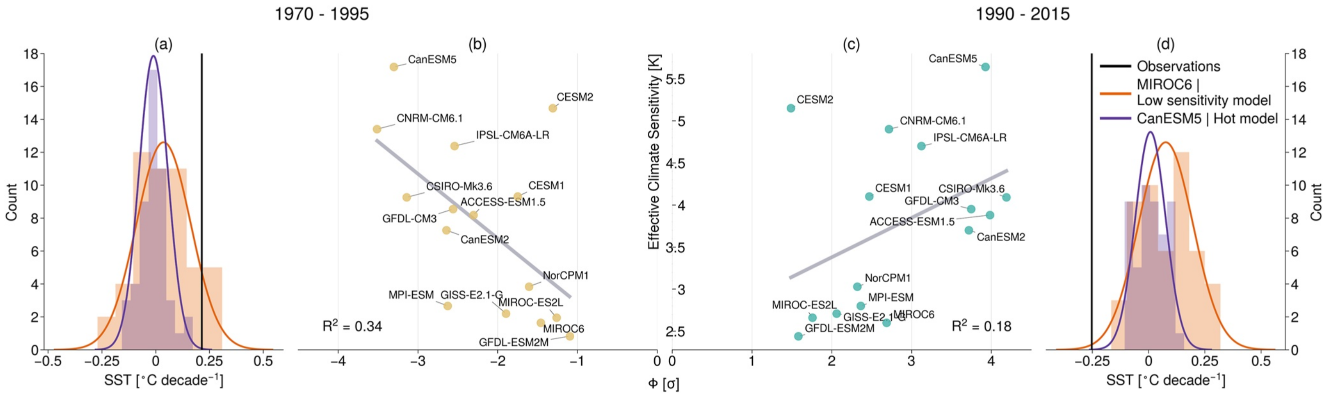

Figure 2. Least-square linear regression of Effective Climate Sensitivity against the difference of the observed gradient changes within the simulated range for each large ensemble (ϕ) for two 25-year trends (b and c). Histograms for both periods show the fitted normal distribution of SST trends used to determine ϕ of two model ensembles for illustration (panel a and d). See Figure S2b in Supporting Information S1 for the multi-model mean value of ϕ for all time periods and trend lengths and Figure S4 in Supporting Information S1 for the coefficient of determination and regression slope for all time periods and trend lengths. The coefficient of determination for a regression without the outlier CESM2 is 0.63 for 1970–1995 an 0.45 for 1990–2015.

Sherwood et al., 2020) and call models with a high EffCS "hot models." EffCS measures the sensitivity of models with a long-term surface warming pattern projected toward the end of the 21st century or apparent in idealized CO_2-step-forcing simulations, which is very different from the one observed over the last 70 years.

For illustration, we pick two 25-year periods centered around the weakening of the gradients in the 1980s and the strengthening of the gradients around the 2010s, while our findings hold for various trend lengths (Figure S4 in Supporting Information S1). Hot models tend to rarely or never reproduce both observed swings in the gradient, because of a narrow spread in trends due to internal variability (Figures 2a and 2d). We speculate how this might come about: the model spread in EffCS is dominated by shortwave cloud feedbacks (Cess et al., 1990) and has been traced to tropical- and subtropical marine low clouds. Their radiative feedbacks are mainly controlled by two competing factors acting on multi-decadal timescales (e.g., Ceppi & Nowack, 2021; Cesana & Del Genio, 2021; Forster et al., 2021a; Klein et al., 2017; Myers et al., 2021, 2023, see illustration in Figure S5 of Supporting Information S1): first, remote warming in the tropical regions of deep convection follows the moist adiabat and warms the entire tropical troposphere, resulting in an increase in the boundary layer inversion strength in the eastern tropical and subtropical Pacific. This negative "inversion feedback" increases low cloud extent and reflected solar radiation and plays a role in establishing the magnitude of the SST gradient on decadal timescales (e.g., Bellomo et al., 2014; Clement et al., 2009; Klein et al., 2017). Second, local sea surface warming underneath the stratocumulus cloud deck destabilizes the boundary layer which, in turn, reduces cloud extent and increases solar absorption, constituting a positive "SST feedback". Climate models do not explicitly resolve but parameterize cloud, boundary layer, and deep convective processes and thus, have a large spread in the relative impacts of the inversion versus the SST feedbacks (e.g., Forster et al., 2021b; Myers et al., 2021).

Consider case A in which internal ocean dynamics, for example, strengthen the gradient with the west warming and the east cooling. Both the SST feedback and the inversion feedback would further cool the SSTs in the eastern tropical Pacific and amplify the gradient. Models with strong inversion feedback would have the strongest changes in gradient. Now consider case B in which forced climate change is initially fairly homogeneous. In this case, a model's SST feedback reduces low cloud cover and further warms the east, while the inversion feedback still increases the low cloud cover and hence dampens the warming in the East. Models with a strong inversion feedback may fully compensate for the positive SST feedback, but in models with a weak inversion feedback the SST feedback dominates the net response (e.g., Klein et al., 2017; Myers et al., 2023). Hence, the model with a strong inversion feedback will have less of a reduction or even an increase in low level cloud and thus, less global mean warming. In this thought exercise, models with a strong inversion feedback would more likely reproduce the observed decadal scale swings while warming moderately under forced climate change. Models with a weak inversion feedback are less likely to reproduce observed decadal scale swings and do not strongly counteract the positive SST feedback under forced warming with their inversion feedback—these are most likely the "hot models." The ability of models to reproduce the observed swings may also be related to their relative amplitudes of variability in the West Pacific (invoking the negative inversion feedback) compared to the East

Pacific (invoking the positive SST feedback). Most models have too much ENSO variability in the West Pacific, while CESM2 (a notable outlier in Figure 2) has too strong variability in the Central and East Pacific (Capotondi et al., 2020; Maher et al., 2023; Samanta et al., 2018).

3. Outlook and Summary

The relationship between a model's climate sensitivity and its ability to reproduce swings in the gradient is intriguing and raises further questions. For example, the inability of the hot models to reproduce the swings is opposite to what we would expect from the fluctuation-dissipation theorem, which states that—in the global mean—systems or models with higher variability also have a higher sensitivity to external forcing (e.g., Cox et al., 2018). Interestingly, the ability of the models to reproduce the observed long-term, slightly negative trend in the gradient does not correlate well with EffCS (Figure S4 in Supporting Information S1) or the models' forced response (not shown). Here, we show that none of the models reproduces long-term trends and many models fail to reproduce short-term swings in the gradient between East and West equatorial Pacific Ocean. We show that only the latter problem is related to the models' climate sensitivity: hot models extremely rarely or never reproduce the observed magnitude of the swings in both directions. Future research should determine how these model shortcomings relate to the relative amplitude and sign of SST feedback and inversion feedback and their connection to inter-annual to multi-decadal variability in the Pacific. Further, it is imperative for model evaluation and trust in climate change projections that we determine to what degree observed decadal to multi-decadal trends in the equatorial Pacific are driven by internal variability, aerosol and greenhouse gas forcing and which aspects the models fail to reproduce.

Data Availability Statement

The data that support the findings of this study are openly available. The large ensemble model output is obtained from the Multi-Model Large Ensemble Archive http://www.cesm.ucar.edu/projects/community-projects/MMLEA/. All other model output used here is accessible from the Earth System Grid Federation https://esgf-data.dkrz.de/projects/esgf-dkrz/ and https://esgf-data.dkrz.de/projects/cmip6-dkrz/. The observational data sets can be downloaded at Had-ISST1: https://www.metoffice.gov.uk/hadobs/hadisst/data/download.html (Rayner et al., 2003), COBE: http://psl.noaa.gov/data/gridded/data.cobe.html (Ishii et al., 2005), ERSSTv5: https://www.ncei.noaa.gov/products/extended-reconstructed-sst (Huang et al., 2017). The EffCS values are available through (Zelinka, 2022; Zelinka et al., 2020). Scripts used in this study are available at https://github.com/shreyadhame/pattern-hotmodel (Dhame, 2023).

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References

Bellomo, K., Clement, A., Mauritsen, T., Rädel, G., & Stevens, B. (2014). Simulating the role of subtropical stratocumulus clouds in driving Pacific climate variability. *Journal of Climate*, *27*(13), 5119–5131. https://doi.org/10.1175/JCLI-D-13-00548.1

Cane, M. A., Clement, A. C., Kaplan, A., Kushnir, Y., Pozdnyakov, D., Seager, R., et al. (1997). Twentieth-century sea surface temperature trends. *Science*, *275*(5302), 957–960. https://doi.org/10.1126/science.275.5302.957

Capotondi, A., Deser, C., Phillips, A. S., Okumura, Y., & Larson, S. M. (2020). ENSO and Pacific decadal variability in the community earth system model version 2. *Journal of Advances in Modeling Earth Systems*, *12*(12), e2019MS002022. https://doi.org/10.1029/2019MS002022

Ceppi, P., & Nowack, P. (2021). Observational evidence that cloud feedback amplifies global warming. *Proceedings of the National Academy of Sciences*, *118*(30), e2026290118. https://doi.org/10.1073/pnas.2026290118

Cesana, G. V., & Del Genio, A. D. (2021). Observational constraint on cloud feedbacks suggests moderate climate sensitivity. *Nature Climate Change*, *11*(3), 213–218. https://doi.org/10.1038/s41558-020-00970-y

Cess, R. D., Potter, G. L., Blanchet, J. P., Boer, G. J., Del Genio, A. D., Déqué, M., et al. (1990). Intercomparison and interpretation of climate feedback processes in 19 atmospheric general circulation models. *Journal of Geophysical Research*, *95*(D10), 16601–16615. https://doi.org/10.1029/JD095iD10p16601

Clement, A. C., Burgman, R., & Norris, J. R. (2009). Observational and model evidence for positive low-level cloud feedback. *Science*, *325*(5939), 460–464. https://doi.org/10.1126/science.1171255

Cox, P. M., Huntingford, C., & Williamson, M. S. (2018). Emergent constraint on equilibrium climate sensitivity from global temperature variability. *Nature*, *553*(7688), 319–322. https://doi.org/10.1038/nature25450

Deser, C., Lehner, F., Rodgers, K. B., Ault, T., Delworth, T. L., DiNezio, P. N., et al. (2020). Insights from Earth system model initial-condition large ensembles and future prospects. *Nature Climate Change*, *10*(4), 277–286. https://doi.org/10.1038/s41558-020-0731-2

Dhame, S. (2023). shreyadhame/pattern-hotmodel: v1.0 (v1.0) [Software]. Zenodo. https://doi.org/10.5281/zenodo.10063261

England, M. H., McGregor, S., Spence, P., Meehl, G. A., Timmermann, A., Cai, W., et al. (2014). Recent intensification of wind-driven circulation in the Pacific and the ongoing warming hiatus. *Nature Climate Change*, *4*(3), 222–227. https://doi.org/10.1038/nclimate2106

Forster, P., Storelvmo, T., Armour, K., Collins, W., Dufresne, J.-L., Frame, F., et al. (2021a). The Earth's energy budget, climate feedbacks, and climate sensitivity (Vol. *275*, pp. 923–1054). https://doi.org/10.1017/9781009157896.009

Forster, P., Storelvmo, T., Armour, K., Collins, W., Dufresne, J.-L., Frame, D., et al. (2021b). The Earth's energy budget, climate feedbacks, and climate sensitivity. In V. Masson-Delmotte, P. Zhai, A. Pirani, S. L. Connors, C. Pean, S. Berger, et al. (Eds.), *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. (pp. 923–1054). Cambridge University Press.

Gregory, J. M., Andrews, T., Ceppi, P., Mauritsen, T., & Webb, M. J. (2020). How accurately can the climate sensitivity to CO_2 be estimated from historical climate change? *Climate Dynamics*, *54*(1), 129–157. https://doi.org/10.1007/s00382-019-04991-y

Gregory, J. M., Ingram, W. J., Palmer, M. A., Jones, G. S., Stott, P. A., Thorpe, R. B., et al. (2004). A new method for diagnosing radiative forcing and climate sensitivity. *Geophysical Research Letters*, *31*(3), L03205. https://doi.org/10.1029/2003GL018747

Hausfather, Z., Marvel, K., Schmidt, G. A., Nielsen-Gammon, J., & Zelinka, M. (2022). Climate simulations: Recognize the 'hot model' problem. *Nature*, *605*(7908), 26–29. https://doi.org/10.1038/d41586-022-01192-2

Huang, B., Thorne, P. W., Banzon, V. F., Boyer, T., Chepurin, G., Lawrimore, J., et al. (2017). NOAA extended reconstructed sea surface temperature (ERSST), version 5 [Dataset]. NOAA National Centers for Environmental Information. https://doi.org/10.7289/V5T72FNM

Ishii, M., Shouji, A., Sugimoto, S., & Matsumoto, T. (2005). Objective analyses of sea-surface temperature and marine meteorological variables for the 20th century using ICOADS and the Kobe collection. *International Journal of Climatology*, *25*(7), 865–879. https://doi.org/10.1002/joc.1169

Klein, S. A., Hall, A., Norris, J. R., & Pincus, R. (2017). Low-cloud feedbacks from cloud-controlling factors: A review. *Surveys in Geophysics*, *38*(6), 1307–1329. https://doi.org/10.1007/s10712-017-9433-3

Kostov, Y., Ferreira, D., Armour, K. C., & Marshall, J. (2018). Contributions of greenhouse gas forcing and the Southern Annular Mode to historical Southern Ocean surface temperature trends. *Geophysical Research Letters*, *45*(2), 1086–1097. https://doi.org/10.1002/2017GL074964

Maher, N., Wills, R. C. J., DiNezio, P., Klavans, J., Milinski, S., Sanchez, S. C., et al. (2023). The future of the El Niño–Southern Oscillation: Using large ensembles to illuminate time-varying responses and inter-model differences. *Earth System Dynamics*, *14*(2), 413–431. https://doi.org/10.5194/esd-14-413-2023

Myers, T. A., Scott, R. C., Zelinka, M. D., Klein, S. A., Norris, J. R., & Caldwell, P. M. (2021). Observational constraints on low cloud feedback reduce uncertainty of climate sensitivity. *Nature Climate Change*, *11*(6), 501–507. https://doi.org/10.1038/s41558-021-01039-0

Myers, T. A., Zelinka, M. D., & Klein, S. A. (2023). Observational constraints on the cloud feedback pattern effect. *Journal of Climate*, *36*(18), 6533–6545. https://doi.org/10.1175/JCLI-D-22-0862.1

Olonscheck, D., & Notz, D. (2017). Consistently estimating internal climate variability from climate model simulations. *Journal of Climate*, *30*(23), 9555–9573. https://doi.org/10.1175/JCLI-D-16-0428.1

Olonscheck, D., Rugenstein, M., & Marotzke, J. (2020). Broad consistency between observed and simulated trends in sea surface temperature patterns. *Geophysical Research Letters*, *47*(10), e2019GL086773. https://doi.org/10.1029/2019GL086773

Rayner, N. A., Parker, D. E., Horton, E. B., Folland, C. K., Alexander, L. V., Rowell, D. P., et al. (2003). Global analyses of sea surface temperature, sea ice, and night marine air temperature since the late nineteenth century. *Journal of Geophysical Research*, *108*(D14), 4407. https://doi.org/10.1029/2002JD002670

Samanta, D., Karnauskas, K. B., Goodkin, N. F., Coats, S., Smerdon, J. E., & Zhang, L. (2018). Coupled model biases breed spurious low-frequency variability in the tropical Pacific Ocean. *Geophysical Research Letters*, *45*(19), 10609–10618. https://doi.org/10.1029/2018GL079455

Seager, R., Cane, M., Henderson, N., Lee, D.-E., Abernathey, R., & Zhang, H. (2019). Strengthening tropical Pacific zonal sea surface temperature gradient consistent with rising greenhouse gases. *Nature Climate Change*, *9*(7), 517–522. https://doi.org/10.1038/s41558-019-0505-x

Seager, R., Henderson, N., & Cane, M. (2022). Persistent discrepancies between observed and modeled trends in the tropical Pacific Ocean. *Journal of Climate*, *35*(14), 4571–4584. https://doi.org/10.1175/JCLI-D-21-0648.1

Sherwood, S. C., Webb, M. J., Annan, J. D., Armour, K. C., Forster, P. M., Hargreaves, J. C., et al. (2020). An assessment of Earth's climate sensitivity using multiple lines of evidence. *Reviews of Geophysics*, *58*(4). https://doi.org/10.1029/2019RG000678

Watanabe, M., Dufresne, J.-L., Kosaka, Y., Mauritsen, T., & Tatebe, H. (2021). Enhanced warming constrained by past trends in equatorial Pacific sea surface temperature gradient. *Nature Climate Change*, *11*(1), 33–37. https://doi.org/10.1038/s41558-020-00933-3

Wills, R. C. J., Dong, Y., Proistosecu, 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

Zelinka, M. D. (2022). mzelinka/cmip56_forcing_feedback_ecs [Software]. Zenodo. https://doi.org/10.5281/zenodo.6647291

Zelinka, M. D., Myers, T. A., McCoy, D., Po-Chedley, S., Caldwell, P. M., Ceppi, P., et al. (2020). Causes of higher climate sensitivity in CMIP6 models. *Geophysical Research Letters*, *47*(1), e2019GL085782. https://doi.org/10.1029/2019GL085782

Zhang, L., Delworth, T. L., Cooke, W., & Yang, X. (2019). Natural variability of Southern Ocean convection as a driver of observed climate trends. *Nature Climate Change*, *9*(1), 59–65. https://doi.org/10.1038/s41558-018-0350-3

References From the Supporting Information

Bethke, I., Wang, Y., Counillon, F., Keenlyside, N., Kimmritz, M., Fransner, F., et al. (2021). NorCPM1 and its contribution to CMIP6 DCPP. *Geoscientific Model Development*, *14*(11), 7073–7116. https://doi.org/10.5194/gmd-14-7073-2021

Boucher, O., Servonnat, J., Albright, A. L., Aumont, O., Balkanski, Y., Bastrikov, V., et al. (2020). Presentation and evaluation of the IPSL-CM6a-LR climate model. *Journal of Advances in Modeling Earth Systems*, *12*(7), e2019MS002010. https://doi.org/10.1029/2019MS002010

Hajima, T., Watanabe, M., Yamamoto, A., Tatebe, H., Noguchi, M. A., Abe, M., et al. (2020). Development of the MIROC-ES2L Earth system model and the evaluation of biogeochemical processes and feedbacks. *Geoscientific Model Development*, *13*(5), 2197–2244. https://doi.org/10.5194/gmd-13-2197-2020

Jeffrey, S., Rotstayn, L., Collier, M., Dravitzki, S., Hamalainen, C., Moeseneder, C., et al. (2013). Australia's CMIP5 submission using the CSIRO-Mk3. 6 model. *Australian Meteorological and Oceanographic Journal*, *63*(1–13), 1–14. https://doi.org/10.22499/2.6301.001

Kay, J. E., Deser, C., Phillips, A., Mai, A., Hannay, C., Strand, G., et al. (2015). The Community Earth System Model (CESM) large ensemble project: A community resource for studying climate change in the presence of internal climate variability. *Bulletin of the American Meteorological Society*, *96*(8), 1333–1349. https://doi.org/10.1175/BAMS-D-13-00255.1

Kelley, M., Schmidt, G. A., Nazarenko, L. S., Bauer, S. E., Ruedy, R., Russell, G. L., et al. (2020). GISS-E2.1: Configurations and climatology. *Journal of Advances in Modeling Earth Systems*, *12*(8), e2019MS002025. https://doi.org/10.1029/2019MS002025

Kirchmeier-Young, M. C., Zwiers, F. W., & Gillett, N. P. (2017). Attribution of extreme events in Arctic sea ice extent. *Journal of Climate*, *30*(2), 553–571. https://doi.org/10.1175/JCLI-D-16-0412.1

10.1029/2023GL105488

Maher, N., Milinski, S., Suarez-Gutierrez, L., Botzet, M., Dobrynin, M., Kornblueh, L., et al. (2019). The Max Planck Institute Grand Ensemble: Enabling the exploration of climate system variability. *Journal of Advances in Modeling Earth Systems*, *11*(7), 2050–2069. https://doi.org/10.1029/2019MS001639

Meehl, G. A., Washington, W. M., Arblaster, J. M., Hu, A., Teng, H., Kay, J. E., et al. (2013). Climate change projections in CESM1 (CAM5) compared to CCSM4. *Journal of Climate*, *26*(17), 6287–6308. https://doi.org/10.1175/JCLI-D-12-00572.1

Rodgers, K. B., Lee, S.-S., Rosenbloom, N., Timmermann, A., Danabasoglu, G., Deser, C., et al. (2021). Ubiquity of human-induced changes in climate variability. *Earth System Dynamics*, *12*(4), 1393–1411. https://doi.org/10.5194/esd-12-1393-2021

Rodgers, K. B., Lin, J., & Frölicher, T. L. (2015). Emergence of multiple ocean ecosystem drivers in a large ensemble suite with an Earth system model. *Biogeosciences*, *12*(11), 3301–3320. https://doi.org/10.5194/bg-12-3301-2015

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. *Journal of Climate*, *31*(19), 7823–7843. https://doi.org/10.1175/JCLI-D-18-0134.1

Swart, N. C., Cole, J. N. S., Kharin, V. V., Lazare, M., Scinocca, J. F., Gillett, N. P., et al. (2019). The Canadian Earth system model version 5 (CanESM5.0.3). *Geoscientific Model Development*, *12*(11), 4823–4873. https://doi.org/10.5194/gmd-12-4823-2019

Tatebe, H., Ogura, T., Nitta, T., Komuro, Y., Ogochi, K., Takemura, T., et al. (2019). Description and basic evaluation of simulated mean state, internal variability, and climate sensitivity in MIROC6. *Geoscientific Model Development*, *12*(7), 2727–2765. https://doi.org/10.5194/gmd-12-2727-2019

Voldoire, A., Saint-Martin, D., Sénési, S., Decharme, B., Alias, A., Chevallier, M., et al. (2019). Evaluation of CMIP6 deck experiments with CNRM-CM6-1. *Journal of Advances in Modeling Earth Systems*, *11*(7), 2177–2213. https://doi.org/10.1029/2019MS001683

Ziehn, T., Chamberlain, M. A., Law, R. M., Lenton, A., Bodman, R. W., Dix, M., et al. (2020). The Australian Earth system model: ACCESS-ESM1.5. *Journal of Southern Hemisphere Earth Systems Science*, *70*(1), 193–214. https://doi.org/10.1071/ES19035