## ETHzürich

# Systematic climate model biases in the large-scale pattern of sea-surface temperature and sea-level pressure change <u>Robert Jnglin Wills</u><sup>1</sup>, Yue Dong<sup>2</sup>, Cristian Proistosescu<sup>3</sup>, Kyle Armour<sup>1</sup>, David Battisti<sup>1</sup> <sup>1</sup>ETH Zürich, <sup>2</sup>University of Colorado Boulder, CIRES, <sup>3</sup>University of Illinois, <sup>3</sup>University of Washington Correspondence: r.jnglinwills@usys.ethz.ch

### **1 Key Points**

• **The bad:** Observed sea-surface temperature and sea-level pressure trends (1979-2020) are at the edge of what climate model large ensembles can simulate in many regions and indices

• The ugly: A signal-to-noise maximizing pattern analysis isolates a pattern

### **3 Trends in Large-Scale Climate Indices**

(a) <i>SST<sub>WP</sub> – SST<sub>EP</sub></i>		Model	Scenarios	N
0.5		E CESM1.1	Historical, RCP8.5	40
E A A A A		CanESM2	Historical, RCP8.5	50
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🖻 💛 –0.5 - 🦻 🕴 🖡 🛔		GFDL-CM3	Historical, RCP8.5	20
-1.0		GFDL-ESM2N	I Historical, RCP8.5	30
1.0		MPI-ESM1.1	Historical RCP8.5	100

of changes that occurred in observations that models are unable to reproduce. This pattern includes Southern Ocean cooling and Pacific SST gradient strengthening, and not a single ensemble member reproduces trends in simple indices of both of these changes

• Why it matters: This has important implications for climate sensitivity (Dong et al. 2019; Armour et al. 2024) and regional rainfall patterns

#### **2 Testing Trends vs Internal Variability**





The observed combination of Pacific SST

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CESS-ESM1. ESM5 SM2.1 RM-CM6-1 Earth3	5 Historical, SSP2-4.5 13 Historical, SSP3-7.0 25 Historical, SSP3-7.0 99 Historical, SSP2-4.5 10 Historical, SSP5-8.5 50 Historical, SSP3-7.0 10
L-CM6A-LR ROC6 ROC-ESM2L CPM1	Historical, SSP3-7.010Historical, SSP3-7.011Historical, SSP5-8.550Historical, SSP2-4.530Historical, SSP2-4.530
ACCESS CanESM2 CanESM5 CESM1 CESM2 CNRM-CM6 CSIRO-MK36 C-Earth3 FDL-CM3 FDL-ESM2M GISS-E21G PSL-CM6A MIROC6 AIROC6 AIROC-ESM2L	<ul> <li>○ ERSSTv5</li> <li>△ AMIPII</li> <li>◇ COBE</li> <li>○ ERA5</li> <li>△ JAR55</li> <li>○ ERSSTv5, ERA5</li> <li>△ ERSSTv5, mean obs-PSL</li> <li>◇ mean obs-SST, ERA5</li> </ul>

Figure 2. Comparison of observed trends in key SST and SLP indices with those in all en- semble members from 16 climate model LEs: (a) the Pacific SST gradient index used in ref. (Watanabe et al., 2021), defined as the difference between the western equatorial Pacific (110°E-180°, 5°S-5°N) and eastern equatorial Pacific (180°-80°W, 5°S-5°N); (b) the ratio of Warm Pool SST warming to global-mean SST warming, which ref. (Dong et al., 2019) showed plays a critical role in global radiative feedbacks; (c) SST in the southeast Pacific (140°W-70°W, 62°S-47°S), which is shown in Fig. 1 to be a region of highly anomalous observed trends; (d) the Walker Cir- culation strength, defined as in (Vecchi et al. 2006) as the difference in SLP between the eastern equatorial Pacific (160°W-80°W, 5°S-5°N) and western equatorial Pacific (80°E-160°E; 5°S - 5°N); (e) the signal-to-noise maximizing pattern index shown in Fig. 3. Violin plots from each model can be compared with multiple observational products, which are shown on the right-hand side. Ensemble averages for each index in each model are shown with a black circle.

**Figure 1.** Observed trends in annual-mean (a) SST and (b) SLP over 1979–2020 from ERSSTv5 (Huang et al., 2017) and the ERA5 reanalysis (Hersbach et al., 2020), respectively. Modeled trends in (c) SST and (d) SLP over 1979–2020, from the multi-model ensemble mean of historical simulations with 16 climate model LEs (Table 1). **The SST trends in each simulation have been rescaled such that their global mean matches that in ERSSTv5.** Observed trends in (e) SST and (f) SLP over 1979–2020 expressed in ensemble standard deviations away from the multi-model ensemble mean (i.e., the difference in trends between observations and the multi-model ensemble mean divided by the square root of the multi-model mean of the variance in trends within each large ensemble). Panels (c)-(f) are computed with the first 10 members of each large ensemble such that each model is weighted equally. The ±2 standard deviation contour is shown with a black line.

• Values greater than ±2 ensemble standard deviations have <5% chance of occuring due to internal variability as represented in the models, but beware of multiple testing

#### **5 Discussion and Conclusions**

#### **Conclusions and Implications:**

• Models either have biases in their forced SST and SLP responses, have too weak multidecadal variability, or some combination of both

• The observed warming pattern favors low cloud increases in the eastern Pacific that bias estimates of ECS based on observations low (assuming East Pacific and Southern Ocean warm eventually) (Armour, Proistosescu et al. 2024)

gradient strengthening and Southern Ocean cooling is well outside the range of what any ensemble member simulates

### **4** Spatiotemporal Evolution of Discrepancy







 This analysis isolates the pattern contributing most to the trend pattern discrepancy

#### **Possible interpretations:**

- East Pacific and South Pacific decadal variability is larger in the real world than in models (Laepple & Huybers 2014)
- The ocean thermostat mechanism is stronger in the real world than in models (Heede & Fedorov 2023), potentially related to mean-state biases
   (Seager et al. 2019)
  - Too weak or incorrect pattern of response to aerosol, volcanic, ozone, or meltwater forcing (Smith et al. 2016; Dong et al. 2022)

**Figure 3.** First multi-field (SST and SLP) signal-to-noise maximizing pattern of a signal-to-noise maximizing pattern analysis that maximizes the ratio of signal to noise, where signal is defined as the difference between observations and the multi-model ensemble mean (on 5-yr and longer timescales) and noise is defined as intra-model and inter-model differences. The orange timeseries show the amplitude of anomalies in this pattern in ERSSTv5/ERA5 relative to the multi-model ensemble mean and the black lines show the amplitude of anomalies in this pattern in the other 4 combinations of SST and SLP observational products. The grey lines show the amplitude of these patterns in each of the 598 simulations from the multi-model ensemble. Normalization is such that the orange line has unit standard deviation and the SST/SLP pattern shows the anomalies associated with a 1-standard-deviation anomaly in the associated index.

• If the observed SST trend is a transient forced response and models have the correct equilibrium SST pattern, this implies a larger pattern effect in the real world than models, and this will bias near-term regional climate projections

Is the tropical SST pattern and Walker circulation response a robustly established model trend bias? Or more than one due to multiple indices that it shows up in? What more is needed? Note that in Rugestein et al. 2023 we test the sensitivity to the trend start and end year (figure on right)
How do we make progress on figuring out the cause of the discrepancy when no model gets it right? (however, see Pedro DiNezio's talk for a model that gets it right)



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