

Supporting Information for

Global emergence of regional heatwave hotspots outpaces climate model simulations

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Figures S1 to S12 Tables S1

Fig. S1 Daily maximum temperature anomalies during recent record-breaking heatwaves and their temporal context. a 2-meter daily maximum temperature anomaly fields (Tx) of the Northern Hemisphere averaged over the 2023 Siberian heatwave. Regions where values were

- record-breaking during the indicated time-period are hatched. **b** Time series for the years 1950 of the hottest annual Tx anomaly relative to 1981 - 2010 June - August averaged over the
- region indicated by the box in **a**. The record-breaking values of regional-mean Tx and their dates are highlighted (red dot) in each time series**. c,d** same as **a, b** but for the Southeast Asian

Heatwave of 2024.

- ERA5 (1958-), JRA55 (1958-), ERA5 (1980-), JRA55 (1980-), MERRA2 (1980-) slopes > 0
- ERA5 (1958-) slope significant (α =0.05)
- ERA5 (1958-) slope $> 90p$ model spread

- 14 **Figure S2 Global map displaying the robustness of regional tail widening and model biases ranked by seven conditions.** The conditions are as follows: Conditions 1-5 positive trends
- 16 across reanalysis datasets and time periods (i. ERA5 (1958-2022), ii. JRA-55 (1958-2022), iii. ERA5 (1980-2022), iv. JRA-55 (1980- 2022), v. MERRA2 (1980 - 2022)**,** vi. significant long-term
- 18 trend in ERA5 (1958- 2022, $p < 0.05$), which is also vii. stronger in magnitude than the 90th percentile of the model spread (n=49). Regions around areas of interest are outlined above
- 20 (numbered 1-20). These regions were tested for trends in their regional averages. Regions outlined in black (1, 2, 3, 4, 5, 6, 8), meet the region-average conditions listed on the bottom right,
- 22 and were therefore selected to be discussed in detail in the main manuscript (Figs. 2, 3, S5). Regions 9-20 fail one of the conditions and are therefore omitted. For completeness, trends and
- 24 boxplots for all regions are provided in Fig. S3. and Fig. S4.

- 26 **Figure S3** Regional timeseries in tail widening and a comparison of distributions of modelled changes over three different time-periods and corresponding reanalysis and gridded station
- 28 observation (E-OBS, nClimGrid) datasets. Definitions of regions 1-10 are shown in Fig. S1. An analysis of regions 11-20 is provided in Fig. S3. Regions that do not meet all the selection criteria 30 are outlined in red.

- 32 **Figure S4** As in S3 but for regions 11-20. Regional timeseries in tail widening and a comparison of distributions of modelled changes over three different time-periods and corresponding 34 reanalysis and gridded station observation (E-OBS, nClimGrid) datasets. Definitions of regions
	- 11-20 are shown in Fig. S1. Regions that do not meet all the selection criteria are outlined in red.

- **Figure S5** As in Figure 3b–k but including three SST-forced large ensembles (60 members in total) outside of the 49 HighResMIP project model runs provided in Fig. 3 (note that panel letters are kept in line with Fig. 3 to facilitate comparison). In each panel, the first two boxplots and the
- as in Figure 3b–k. The third boxplot displays regional trends from a 10-member ensemble of CAM6 forced by ERSSTv5 historical SSTs, covering 1958–2021. The fourth boxplot shows the

ERA5 (red), JRA-55 (orange), and E-OBS (yellow) datapoints and uncertainty range are exactly

- same from a 25-member ensemble of ECHAM5 forced by ERSSTv5 covering 1958–2020, and the fifth from a 25-member ensemble of ECHAM5 forced by Hurrell SSTs covering 1958–2020.
- Note that each of the three extra ensembles shown here do not cover the entire time-period 1958– considered in the main analysis. The sixth boxplot aggregates all 109 model realizations.
- The ECHAM5 runs [\(Roeckner](https://pure.mpg.de/rest/items/item_995269_4/component/file_995268/content) et al., 2003) were accessed through the NOAA Facility for [Weather](https://psl.noaa.gov/repository/facts/) and Climate [Assessments](https://psl.noaa.gov/repository/facts/) (FACTS) repository [\(Murray](http://10.1175/BAMS-D-19-0224.1) et al., 2020). The [CAM6](https://www.cesm.ucar.edu/working-groups/climate/simulations/cam6-prescribed-sst) runs were
- accessed through the NCAR Climate Data [Gateway](https://www.earthsystemgrid.org/dataset/ucar.cgd.cesm2.cam6.prescribed_sst_amip.html) thanks to the NCAR Climate Variability & Change Working Group (CVCWG).

- 58 **Figure S6** Demonstration of procedure to calculate smoothed global mean near surface temperature (GMST) time series for each model realization and observations, which are used as
- 60 a trend covariate instead of time in Figs. S3–S4. In **a**, the thin red line shows the global mean (land and ocean points included) of each grid point's annual median Tx. The thick red line shows
- 62 this time series smoothed by a low-pass filter to retain only variability of frequencies over 10 years (i.e. a 10-yearly cutoff, third-order Butterworth filter, applied forward and backward). In **b**, this
- 64 smoothed time series is compared against the widely-used NASA GISTEMP v4 GMST time series, subject to the same smoothing (and with the time-means of each over the whole 1950–
- 66 2022 period removed). Their high similarity justifies the use of Tx data and annual medians to generate the GMST time series. Light and dark gray lines in **a** and **b** show smoothed GMST time
- 68 series for model data.

Figure S7 As in Fig. 2a but **a** multi-model mean trend in the changes in the differences of the 72 hottest 2% of annual maximum of daily maximum temperature (Tx) per year with the average of the 25% of days (annual 87.5th percentile of Tx) percentile of the annual maximum temperature 74 at each grid point for years 1950-2022 (as Fig. 2a but for models) **b** the same variables but scaling

local temperatures with global mean temperatures.

Resolution and experiment forcing subgroup comparisons for model ys, observed trends (in YEAR)

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Figure S8 Observed trends in comparison with the models used and distinguished by their 78 **resolution and to atmosphere-ocean coupling frameworks a, b, d, e** Comparison of observed trends (ERA5) in the widening of the upper quartile (see Fig. 3a) in a range of different model

- 80 subsets and architectures provided **c, f** Collapsing the maps in **a, b, d, e** into histograms. In **c**, histograms provide estimates of the global distribution of the percentages provided in a and b.
- 82 Color values match the color map provided in the bottom of the figure comparing models with high (n=25) and low resolution (n=24). A high percentage value for the $25th - 75th$ percentile
- 84 signifies a better agreement with trends based on reanalysis, while high values in the lower (upper) percentiles relate to an under (over) estimation of trends in models, on a gridcell-by-
- 86 gridcell basis. The histograms in **f** show the same for trends over land area based on coupled (n-16) vs. SST-forced experiments (n=33). **d** and **e**, respectively.

Resolution and experiment forcing subgroup comparisons for model vs. observed trends (in GMST)

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Figure S9 As in Fig. S8 but for GMST level covariate instead of years. a, b, d, e Comparison 90 of observed trends (ERA5) in the widening of the upper quartile (see Fig. 3a) in a range of different model subsets and architectures provided **c, f** Collapsing the maps in **a, b, d, e** into histograms. 92 In **c**, histograms provide estimates of the global distribution of the percentages provided in a and

- b. Color values match the color map provided in the bottom of the figure comparing models with
- 94 high (n=25) and low resolution (n=24). A high percentage value for the $25th 75th$ percentile signifies a better agreement with trends based on reanalysis, while high values in the lower
- 96 (upper) percentiles relate to an under (over) estimation of trends in models, on a gridcell-bygridcell basis. The histograms in **f** show the same for trends over land area based on coupled (n-
- 98 16) vs. SST-forced (n-33) experiments. **d** and **e**, respectively.

Figure S10 Comparison of global fraction of land area with **a** positive trends, **b** positive trends 102 which are statistically significant (p < 0.05) and **c** the fraction of positive trends which are also statistically significant (p < 0.05) (right y-axis). **d** Fraction of global land area over which positive 104 trends are significant with a p-value of p < 0.01 and **c** the respective fraction compared to all grid points with positive trends (right y-axis).

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108 **Fig. S11** Alternative depiction of data shown in Fig. 4 providing a histogram of all models combined in **a** and cumulative density distributions in **b** across positive and negative trends 110 instead of providing values for each side of the distribution separately. Trends that exceed 0.5 0.5 °C/decade irrespective of sign are underestimated by a factor of 3.5.

Figure S12 Modelled trends in the hottest 2% compared to the upper 25% for an ensemble 116 member based on HadGEM3. Strong trends are visible in single grid-points in Arctic regions and might be related to modelled singularities linked to assumptions around land and/or sea ice 118 coverage.

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Table S1: Model runs and characteristics used in this analysis. Note that some models feature 122 more than one ensemble member.

