

# Supporting Information for “Detecting climate signals using explainable AI with single-forcing large ensembles”

Zachary M. Labe<sup>1</sup> and Elizabeth A. Barnes<sup>1</sup>

<sup>1</sup>Department of Atmospheric Science, Colorado State University, Fort Collins, CO, USA

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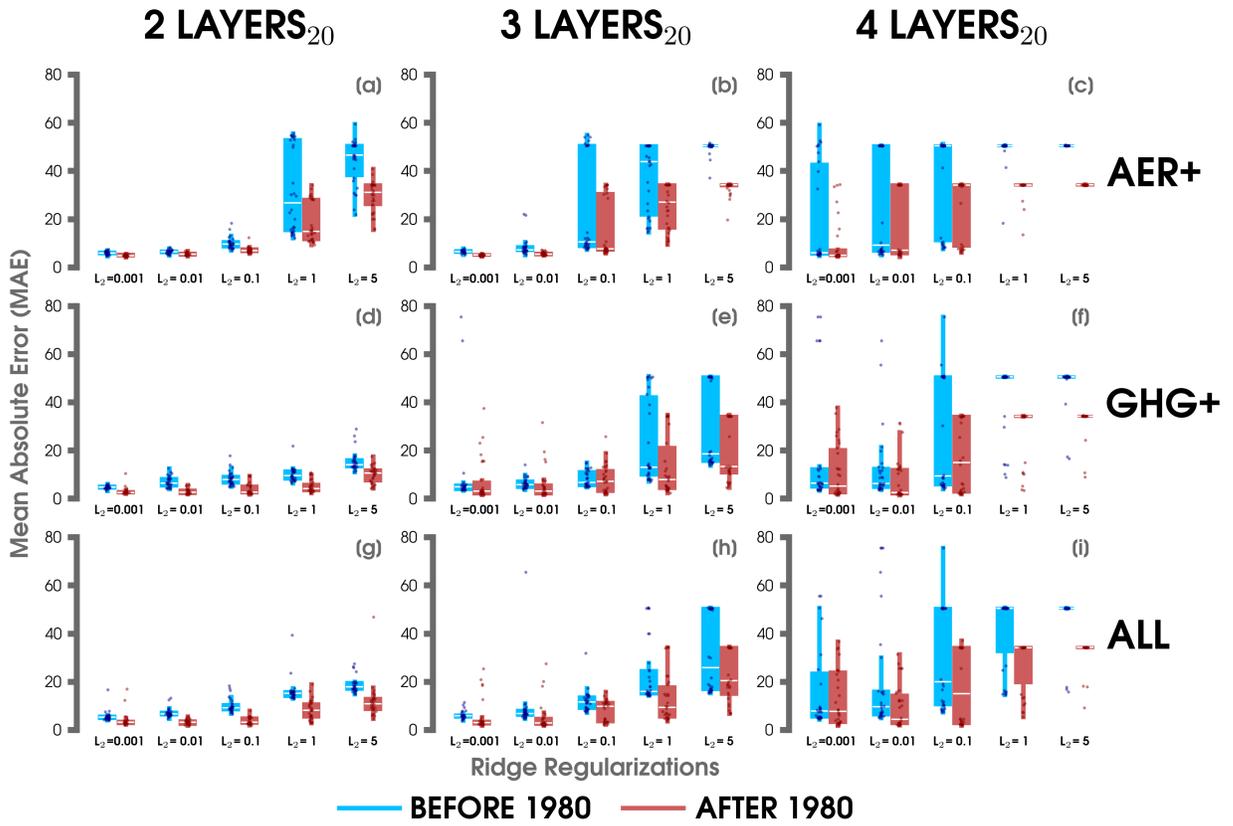
Corresponding author: Zachary M. Labe (zmlabe@rams.colostate.edu)

**Table S.1.** Description of climate model data sets used for the primary analysis in this study.

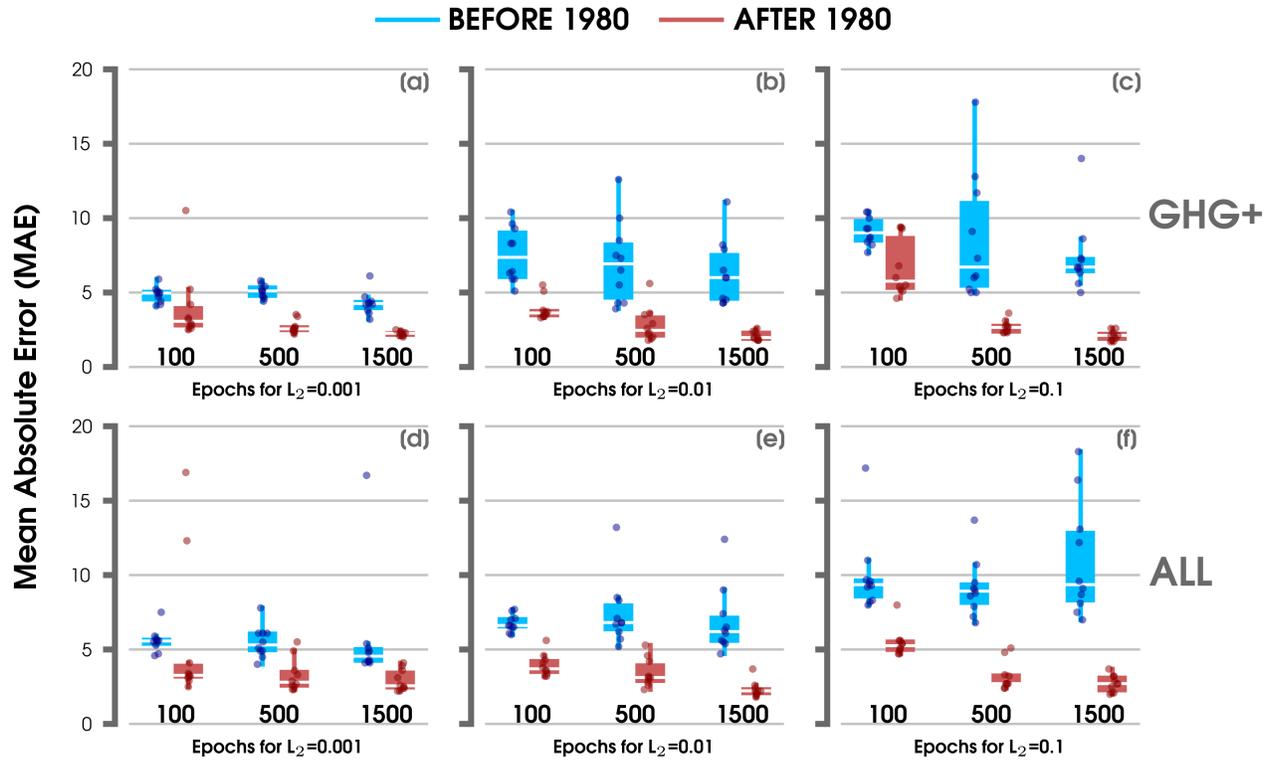
Name	Forcing	Years	# Members	Reference
ALL	Historical (to 2005), RCP 8.5	1920–2080	20	CESM-LE - Kay et al. (2015)
AER+	ALL, but fixed greenhouse gases to 1920 levels	1920–2080	20	XGHG - Deser et al. (2020)
GHG+	ALL, but fixed industrial aerosols to 1920 levels	1920–2080	20	XAER - Deser et al. (2020)

**Table S.2.** Description of observational data sets used for the primary analysis in this study.

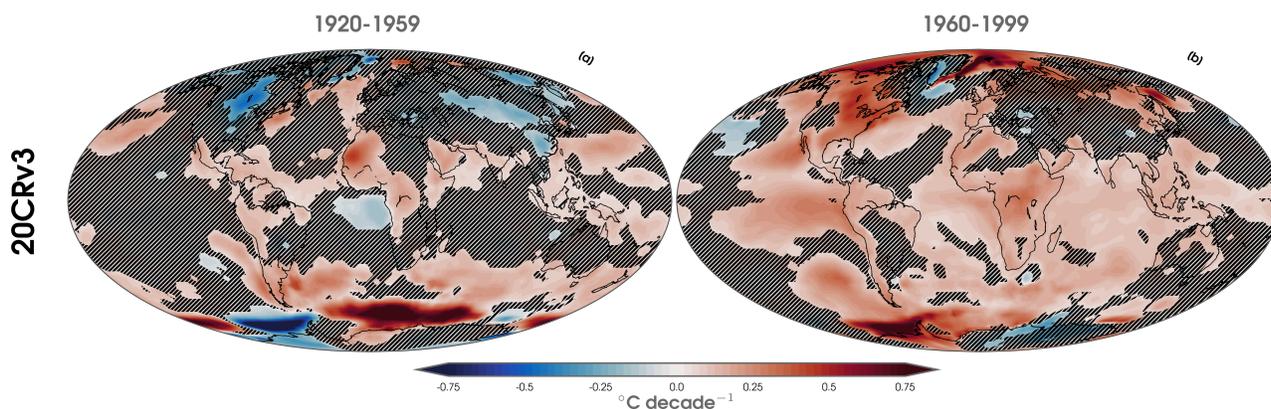
Name	Data Set	Years	Reference
20CRv3	NOAA-CIRES-DOE 20th Century Reanalysis V3	1920–2015	Slivinski et al. (2019)



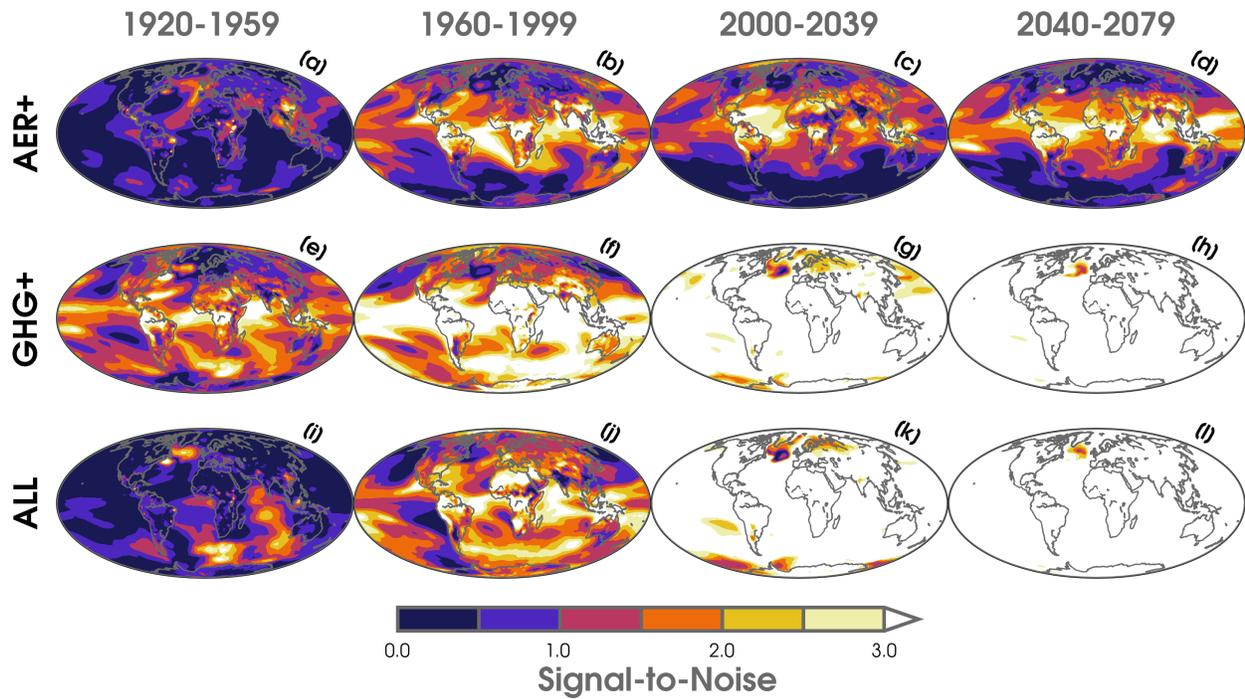
**Figure S.1.** Box-and-whisker plots showing the mean absolute error (MAE) of testing years before 1980 (blue) and after 1980 (red) for the ANNs trained separately on each large ensemble experiment (AER+; a-c, GHG+; d-f, ALL; g-i). Results are shown for ANN architectures using 2 hidden layers of 20 nodes each (a,d,g), 3 hidden layers of 20 nodes each (b,e,h), and 4 hidden layers of 20 nodes each (c,f,i) and different  $L_2$  regularization values (0.001, 0.01, 0.1, 1, 5). Each box-and-whisker distribution of ANNs is comprised of 10 iterations (different combinations of training and testing data and random initialization seeds) for 3 separate epochs (100, 500, 1500).



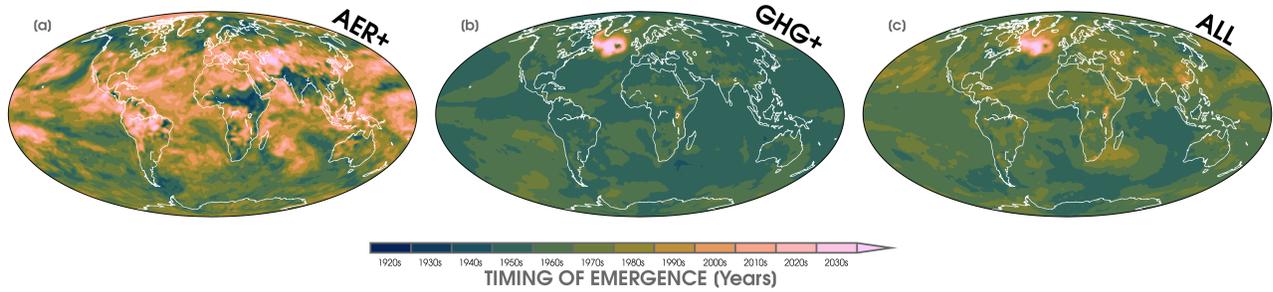
**Figure S.2.** Box-and-whisker plots showing the mean absolute error (MAE) of testing years before 1980 (blue) and after 1980 (red) for the ANNs trained separately on two large ensemble experiments (GHG+; a-c, ALL; d-f) using architectures with 2 hidden layers of 20 nodes each, three different epochs (100, 500, 1500), and L<sub>2</sub> regularization values of 0.001 (a,d), 0.01 (b,e), and 0.1 (c,f). Each box-and-whisker distribution of ANNs is comprised of 10 iterations using different combinations of training and testing data and random initialization seeds.



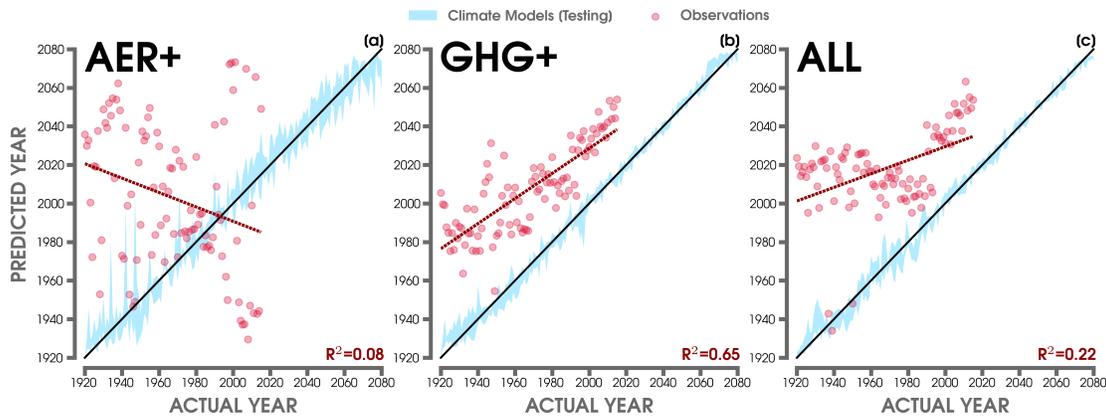
**Figure S.3.** Annual linear least squares trends of 2-m temperature ( $^{\circ}\text{C}$  per decade) over 1920 to 1959 (a) and 1960 to 1999 (b) using 20CRv3 reanalysis (observations). Statistically significant trends are shown with shaded contours at the 95% confidence level following the Mann-Kendall (MK) test (Mann, 1945; Bevan & Kendall, 1971). Insignificant trends are masked out using black hatch marks.



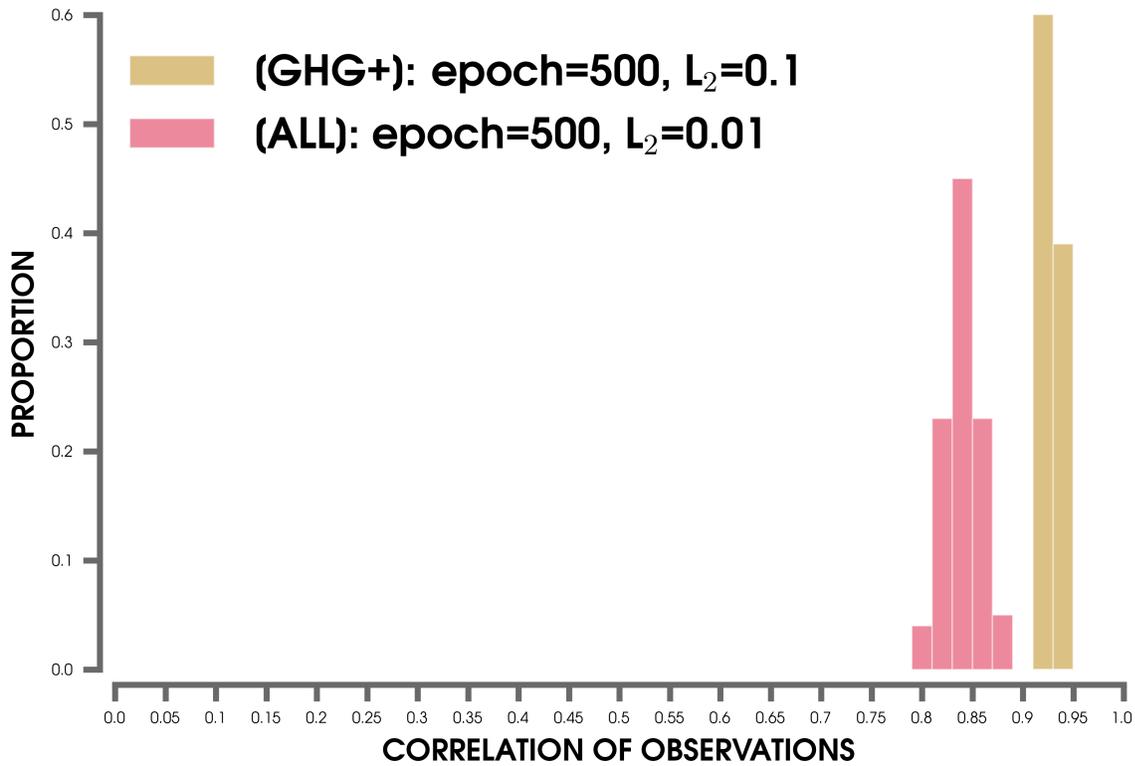
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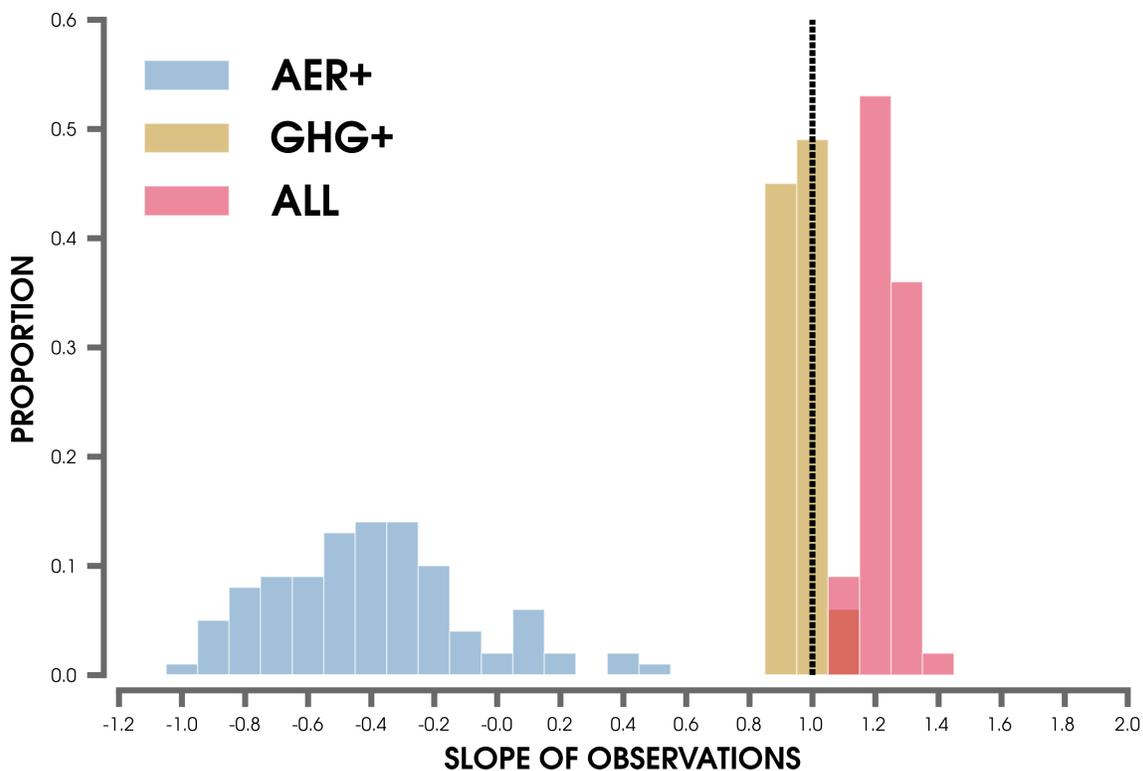
**Figure S.5.** Average timing of emergence (ToE) maps defined as the first year the 10-year running-mean 2-m (annual mean) temperature exceeds and stays above the mean 1920-1949 period by more than two standard deviations (e.g., Lehner et al., 2017) for each ensemble member in the three large ensemble simulations (AER+; a, GHG+; b, ALL; c).



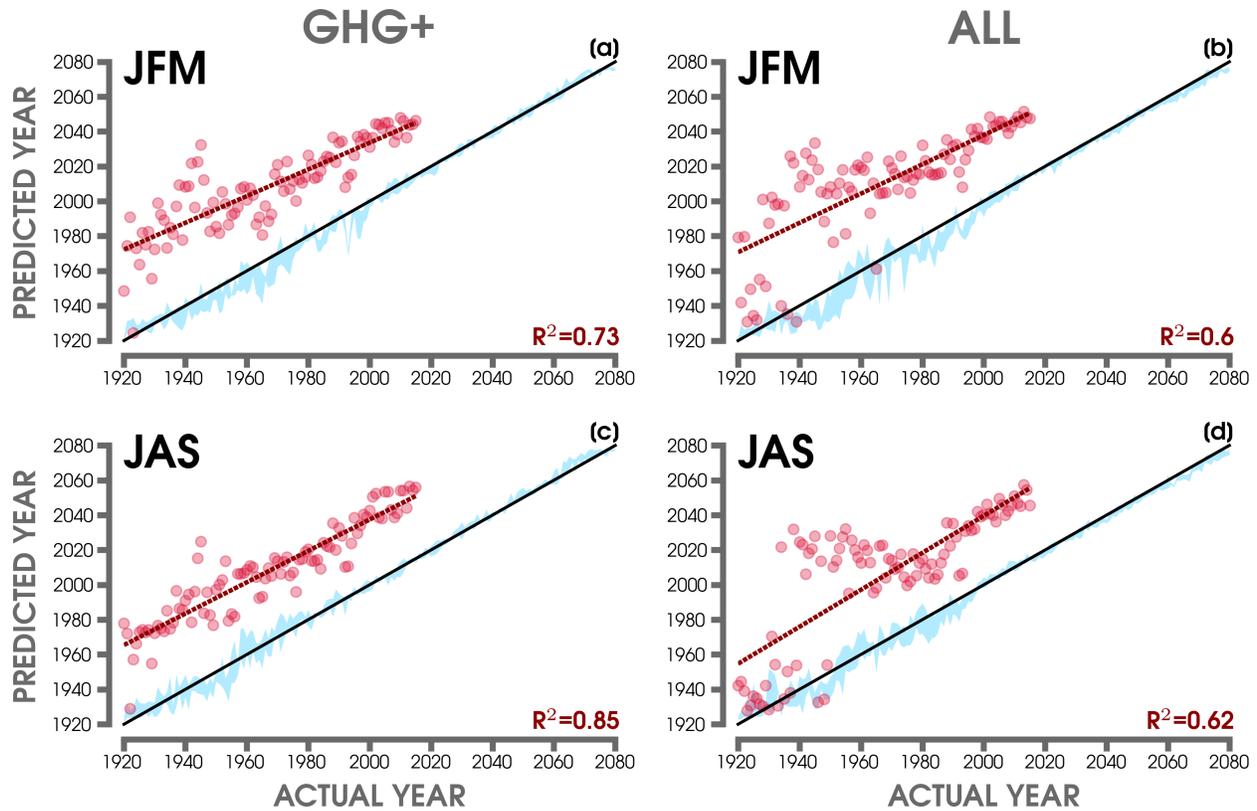
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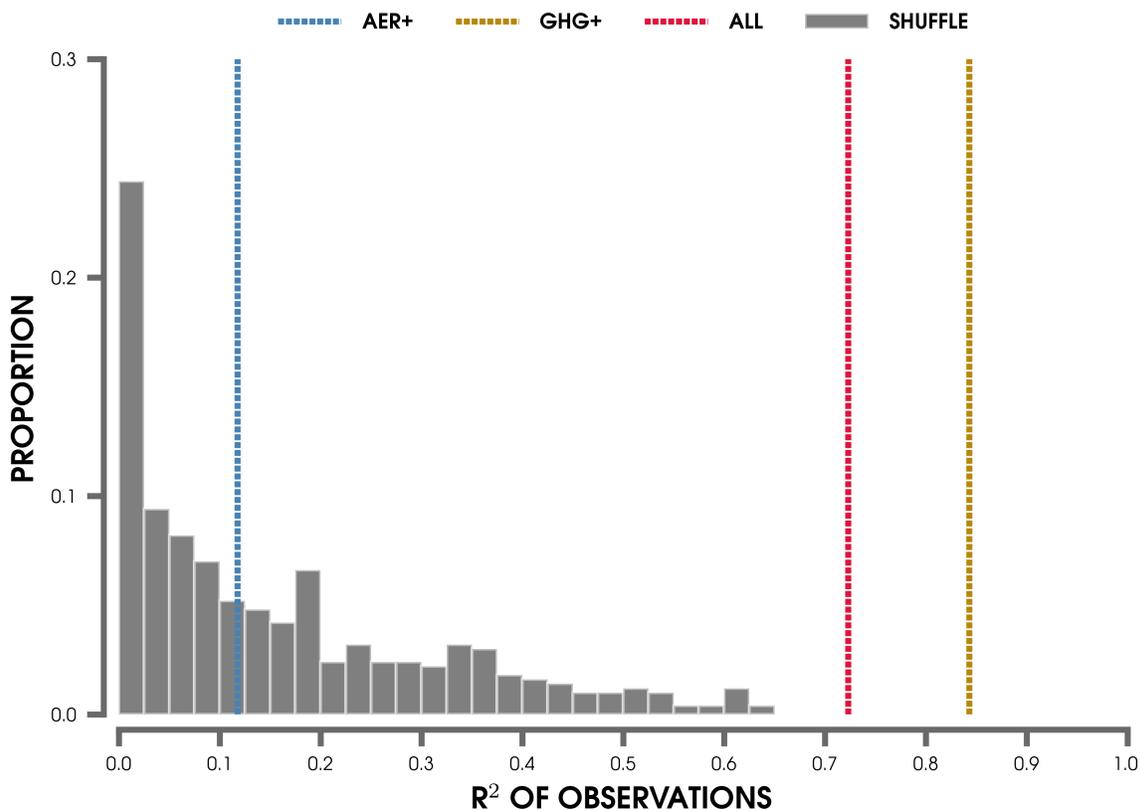
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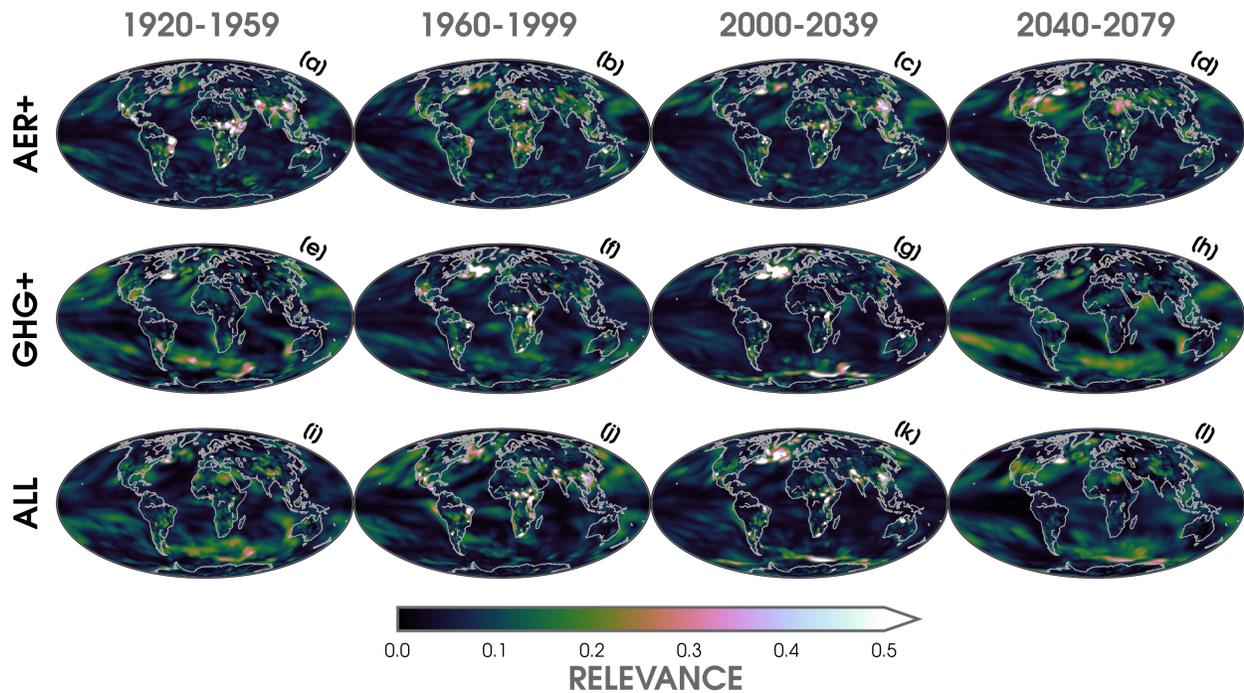
**Figure S.8.** Histogram of the possible slopes of predicted 20CRv3 observations after considering different combinations of training and testing data for each of the AER+ (blue), GHG+ (brown), and ALL (red) ANNs. The 1:1 is highlighted by the dashed gray line.



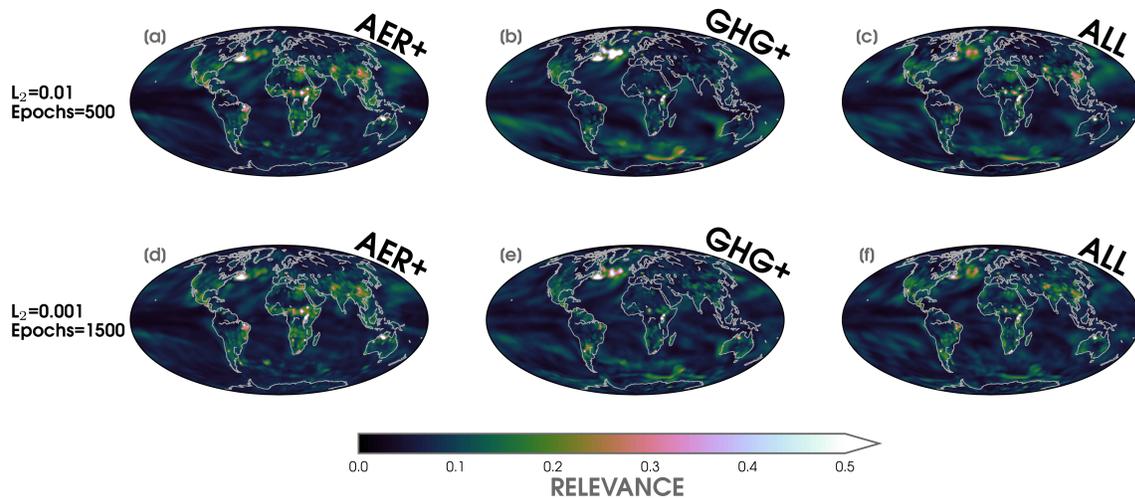
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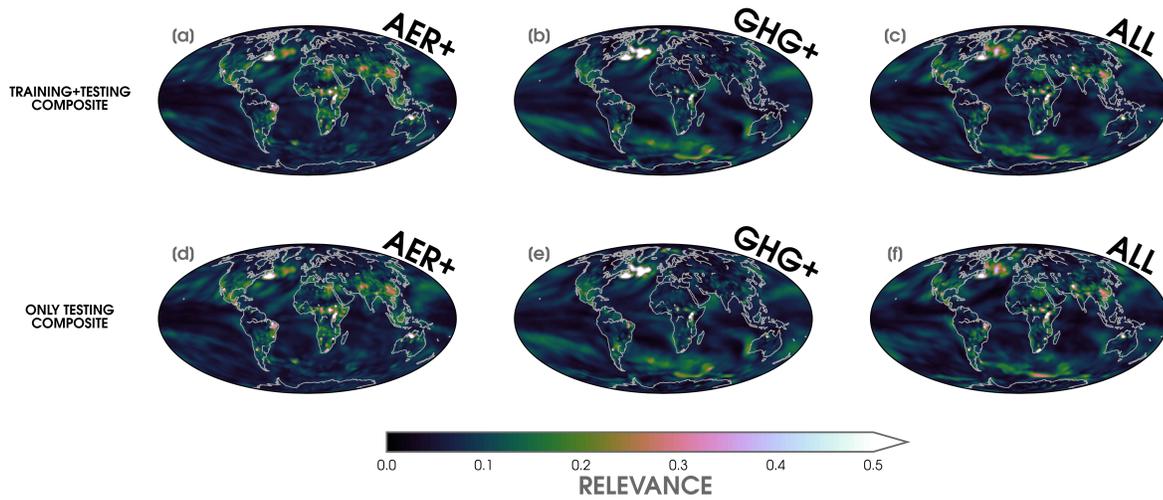
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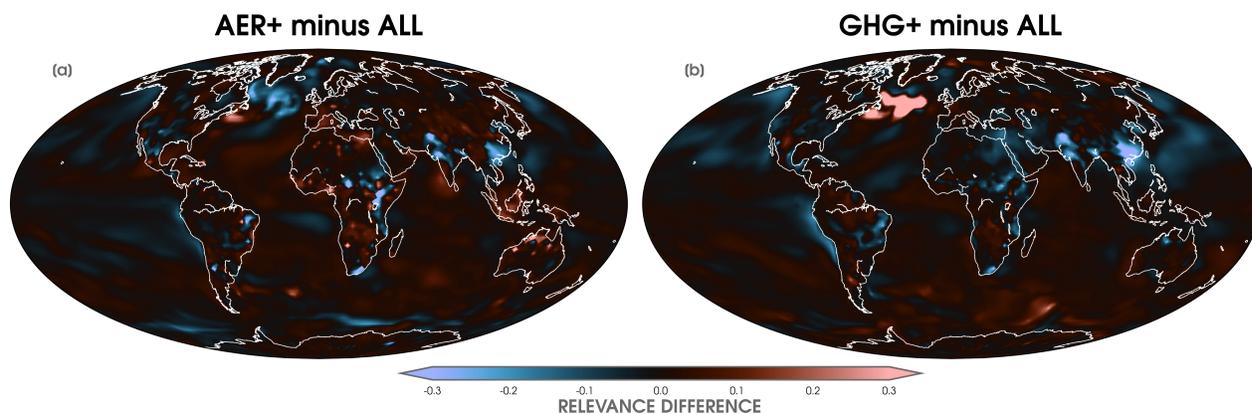
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**Figure S.12.** (a) Composite of LRP heatmaps over 1920 to 2080 for inputs of annual 2-m temperature (global) maps from AER+ using the ANN architecture with 500 epochs and  $L_2$  regularization set to 0.01. (b) Same as (a) but for GHG+. (c) Same as (a) but for ALL. (d-f) Same as top row, but for LRP heatmaps from an ANN architecture with 1500 epochs and  $L_2$  regularization set to 0.001. LRP composites are generated by averaging across 100 possible ANN iterations by using different combinations of training and testing data for each large ensemble. Higher LRP values indicate greater relevance for the ANN’s prediction.



**Figure S.13.** (a) Composite of LRP heatmaps using both training and testing data over 1920 to 2080 for inputs of annual 2-m temperature (global) maps from AER+. (b) Same as (a) but for GHG+. (c) Same as (a) but for ALL. (d-f) Same as top row, but for LRP heatmaps using only testing data. Higher LRP values indicate greater relevance for the ANN’s prediction.



**Figure S.14.** Difference in composites of LRP heatmaps for AER+ minus ALL (a) and GHG+ minus ALL (b) over 1960 to 2039 for inputs of annual 2-m temperature (global) maps. LRP composites are first generated by averaging across 100 possible ANN iterations by using different combinations of training and testing data for each large ensemble.

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