Supplemental Material

Supplemental Material for:

Using climate model simulations to constrain observations

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1. Statistical analysis

The statistical analysis presented in this section closely follows Santer et al. (2011), with only minor modifications to the notation and text.

a. Notation

This section introduces the statistical notation used for comparing atmospheric temperature changes in models, reanalysis, and satellite data in Fig. 8. These comparisons involve least-squares linear trends and regression coefficients, referred to collectively as "metrics". Metrics are calculated for overlapping L-month analysis periods. We consider four specific values of L here: 120, 240, 360, and 480 months. We do not explicitly include the timescale L in our notation.

Abbreviations

MMA	Multi-model average
MMSD	Multi-model sampling distribution of metric
SMSD	Single-model sampling distribution of metric

Subscripts

o	Subscript denoting observationally based data (satellite data or reanalysis)
c	Subscript denoting output from model control runs
f	Subscript denoting output from model forced experiments

Indices

i	Index over number of maximally overlapping analysis periods in observations
j	Index over number of models
k	Index over number of HIST+RCP8.5 or HIST+SSP5 realizations

Sample sizes

L	Length of period for trend/regression calculations (in months)
N_o	Total number of overlapping L-month analysis periods in observed data set (calculated over 1979 to 2019)
N_c	Total number of overlapping L-month analysis periods in control run MMSD
N_f	Total number of overlapping L-month analysis periods in HIST+RCP8.5 or HIST+SSP5 MMSD (calculated over 1979 to 2019)
$N_c(j)$	Total number of overlapping L-month analysis periods in j^{th} model control run (varies with control run length)
N_{mod}	Total number of models (36 and 30 for CMIP5 and CMIP6 control runs; 28 for CMIP5 forced runs; 22 or 21 for CMIP6 forced runs)
$N_r(j)$	Total number of HIST+RCP8.5 or HIST+SSP5 realizations for j^{th} model

Metrics (trends or regression coefficients)

$b_o(i)$	Metric for i^{th} overlapping L-month analysis period in observations
$b_c(i,j)$	Metric for i^{th} overlapping L-month analysis period in j^{th} model control run
$b_f(i,j,k)$	Metric for i^{th} overlapping L-month analysis period from j^{th} model and k^{th} realization of HIST+RCP8.5 or HIST+SSP5 run
$\overline{b_o}$	Average of $b_o(i)$ over all overlapping L-month analysis periods between 1979 and 2019

b. Maximally overlapping analysis periods in Figure 8

As used here and in the main text, 'maximally overlapping' signifies overlap by all but one month. For $L = 120$ months, for example, the first analysis period is over January 1979 to December 1988, the second period is over February 1979 to January 1989, *etc.* All metrics were computed from time series of monthly-mean anomalies of spatially-averaged TLS, corrected TMT, and TLT data. In the satellite and reanalysis data and the HIST+RCP8.5 and HIST+SSP5 simulations, anomalies were defined relative to climatological monthly means over the full 492-month period from January 1979 to December 2019. Control run anomalies were defined relative to climatological monthly means calculated over the full length of each model's control integration.

Here, N_o, N_c, and N_f are the total number of maximally overlapping L-month analysis periods in observations, the control run multi-model sampling distribution (MMSD), and the MMSD of extended HIST simulations (respectively). In each observational record, $N_o = 373$ for $L = 120$ months. For the case of $L = 120$ and CMIP5 control run data, $N_c = 224904$. For $L = 120$ months and CMIP5 HIST+RCP8.5 runs, $N_f = 45879$ (373 maximally overlapping trends $\times$ 123 realizations).

The time series of spatially-averaged temperature anomalies from individual models are not concatenated prior to calculating L-month trends and regression coefficients. Concatenating could spuriously inflate trends and regression coefficients spanning the 'splice point' between two model control runs or two model extended HIST runs with large differences in the amplitude of their variability. Instead, metrics for maximally overlapping analysis periods are calculated separately from each individual model's control run or extended HIST simulation. Metrics for each model are then accumulated in multi-model distributions of unforced and unforced results. These multi-model distributions are shown in Fig. 8.

c. Use of overlapping analysis periods

Our use of maximally overlapping L-month analysis periods has the advantage of reducing the impact of seasonal and interannual noise on the temperature trends and the tropical amplification metric that are of interest here. However, it has the disadvantage of decreasing the statistical independence of the metrics calculated for the individual L-month "sliding windows".

While non-independence of samples is an important issue in formal statistical significance testing, it is not a serious concern here. This is because our metrics are not used as a basis for formal statistical tests. Instead, they simply provide useful information on whether the observed metrics in Fig. 8 are unusually large relative to model-based estimates of unforced metric values, or are unusually small relative to model estimates of metrics obtained from forced runs. Note also that we process observations and model output in identical ways, with the same overlap between successive L-month analysis periods – *i.e.*, we are not generating fundamentally different temporal autocorrelation structure in the model and observational metrics.

Whether we employ overlapping or non-overlapping analysis periods has very small impact on the MMSDs in Fig. 8. This suggests that in both the control runs and the forced runs, the sample sizes of metrics computed from non-overlapping L-month analysis periods are adequate for obtaining reliable estimates of empirical p-values (which are not shown here).

In the case of the observations, however, satellite temperature records are relatively short, and the choice of whether to use overlapping or non-overlapping observed analysis periods can have a large impact on comparisons between modeled and observed metrics. For example, each observational data set contains only four non-overlapping 10-year time series segments. These four segments do not adequately sample the impact of monthly and interannual variability on observed linear trends or regression coefficients. We reduce this sampling variability by using maximally overlapping L-month analysis periods and displaying timescale-average observed results in Fig. 8.

Even with our use of maximally overlapping trends, a 41-year record is clearly sub-optimal for reliable assessment of observed multi-decadal variability. In related work with a wide range of different statistical models of short- and/or long-term memory, however, we find no evidence that either CMIP5 or CMIP6 models systematically underestimate the amplitude of observed decadal-timescale TMT variability (Pallotta and Santer 2020).

d. Model independence

An implicit assumption in Fig. 8 is that results from individual models are independent. This assumption is almost certainly unjustified (Masson and Knutti 2011). While it would be interesting to explore the sensitivity of our results to the selection of different subsets of independent CMIP5 and CMIP6 models, we do not perform such an analysis here. The identification of independent model subsets is likely to be sensitive to the variables, statistical procedures, and metrics used to assess model dependencies (Caldwell et al. 2014).

e. Multi-model average time series, metrics, and spread of metrics

The weighted MMA shown in Fig. 1 is calculated by first computing the average over the $N_r(j)$ HIST+RCP8.5 or HIST+SSP5 realizations of the j^{th} model, and then by averaging results over all N_{mod} models. For the weighted versions of statistical metrics (the RMS differences in Fig. 3, zonal-mean trends in Fig. 5, and MMA trends Figs. 4, 6, and 7), these two separate averaging steps are performed with the individual metrics rather than with the individual time series.

f. Weighting of histograms

All histograms are weighted to account for model differences in either the number of extended HIST realizations or the length of control runs. Without weighting, models with more extended

HIST realizations or with longer control runs would have a disproportionately large effect on the multi-model sampling distributions of trends and regression coefficients.

The histograms in Figs. 6, 8, and 10 were plotted with the Matplotlib pyplot.hist function with arrays of weights and with the "density=True" option.[i] The "density=True" option ensures that "each bin will display the bin's raw count divided by the total number of counts and the bin width... so that the area under the histogram integrates to 1". Two types of weighting were performed, depending on whether the processing involves maximally overlapping analysis periods (as in Fig. 8) or non-overlapping analysis periods (as in Figs. 6 and 10).

In the case of non-overlapping analysis periods and sampling distributions of metrics from model extended HIST runs, the weights passed to pyplot.hist are $1/N_r(j)$, where $N_r(j)$ is the number of realizations for the j^{th} model. In the case of the maximally overlapping analysis periods, the weights for each analysis period of the j^{th} model are $1/N_c(j)$ for control runs and $1/N_r(j)$ for extended HIST runs, where $N_c(j)$ is the total number of maximally overlapping L-month analysis periods for the j^{th} model control run.

The fits to the histograms in Figs. 6, 8, and 10 use kernel density estimation (KDE).[ii] As in the case of the histograms plotted with pyplot.hist, the same weighting and "density=True" option was employed in the KDE (see above). The KDE fits relied on the default Scott bandwidth estimator.

g. Weighted t-test

We performed t-tests to determine whether there are significant differences between the CMIP5 and CMIP6 volcanic TLS signals. Tests were conducted separately for the lower stratospheric temperature signals after the eruptions of El Chichón and Pinatubo. The samples in each test are the CMIP5 and CMIP6 root-mean-square (RMS) errors relative to the observed volcanic TLS signals (see caption of Fig. 3).

As in the case of the weighting of histograms (see Section f), we need to account for model differences in the number of extended HIST realizations. This was done with the Python module statsmodels.stats.weightstats.ttest_ind.[iii] The $1/N_r(j)$ weights are the same as those used in histogram weighting. The t-test was conducted with usevar='unequal', thus allowing for unequal variances in CMIP5 and CMIP6 RMS errors. Our null hypothesis is that there are no significant difference between CMIP5 and CMIP6 volcanic TLS signals. Estimated p-values for this null hypothesis are sensitive to whether or not weights are included (which has substantial influence on the degrees of freedom), but are insensitive to the whether the variances of the CMIP5 and CMIP6 RMS errors are assumed to be equal or unequal.

h. Orthogonal Distance Regression

We used Orthogonal Distance Regression (ODR) to calculate the slopes of the regression fits to the CMIP5 and CMIP6 trend data shown in Fig. 9. ODR has certain advantages relative to the more commonly used Ordinary Least-Squares (OLS) regression.[iv] In general, the regression slopes reported in Fig. 9 were consistently larger when estimated with ODR. For the regression

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[i] https://matplotlib.org/3.3.3/api/_as_gen/matplotlib.pyplot.hist.html

[ii] https://scikit-learn.org/stable/modules/density.html

[iii] https://www.statsmodels.org/stable/generated/statsmodels.stats.weightstats.ttest_ind.html

[iv] See https://docs.scipy.org/doc/scipy/reference/odr.html. We employed the scipy.odr package for ODR performing ODR.

between WV trends and corrected TMT trends in Fig. 9C, for example, OLS yields slopes of 5.1%/decade for both the CMIP5 and CMIP6 ensembles, while the corresponding ODR slopes are 5.3 and 5.5%/decade. Both the OLS and ODR regressions weighted individual trend samples to account for model differences in the number of extended HIST realizations (see Section f).

References

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LIST OF TABLES

TABLE 1: Basic information relating to the start dates, end dates, and lengths (N_m, in months) of the 123 CMIP5 historical and RCP8.5 simulations used in this study. EM is the "ensemble member" identifier (see http://cmip-pcmdi.llnl.gov/cmip5/documents.html for further details).

	Model	EM	Hist. Start	Hist. End	Hist. N_m	RCP8.5 Start	RCP8.5 End	RCP8.5 N_m
1	ACCESS1.0	r1i1p1	1850-01	2005-12	1872	2006-01	2100-12	1140
2	ACCESS1.3	r1i1p1	1850-01	2005-12	1872	2006-01	2100-12	1140
3	BCC-CSM1.1	r1i1p1	1850-01	2012-12	1956	2006-01	2300-12	3540
4	BCC-CSM1.1(m)	r1i1p1	1850-01	2012-12	1956	2006-01	2099-12	1128
5-14	CanESM2 historical r-1	r1i1p1–r10i1p1	1850-01	2005-12	1872	2006-01	2100-12	1140
15-24	CanESM2 historical r-2	r1i1p1–r10i1p1	1850-01	2005-12	1872	2006-01	2100-12	1140
25-34	CanESM2 historical r-3	r1i1p1–r10i1p1	1850-01	2005-12	1872	2006-01	2100-12	1140
35-44	CanESM2 historical r-4	r1i1p1–r10i1p1	1850-01	2005-12	1872	2006-01	2100-12	1140
45-54	CanESM2 historical r-5	r1i1p1–r10i1p1	1850-01	2005-12	1872	2006-01	2100-12	1140
55-57	CCSM4	r1i1p1–r3i1p1	1850-01	2005-12	1872	2006-01	2100-12	1140
58	CESM1-BGC	r1i1p1	1850-01	2005-12	1872	2006-01	2100-12	1140
59-98	CESM1-CAM5	r1i1p1–r40i1p1	1850-01	2005-12	1872	2006-01	2100-12	1140
99	CSIRO-Mk3.6.0	r10i1p1	1850-01	2005-12	1872	2006-01	2100-12	1140
100	EC-EARTH	r8i1p1	1850-01	2012-12	1956	2006-01	2100-12	1140
101	GFDL-CM3	r1i1p1	1860-01	2005-12	1752	2006-01	2100-12	1140
102	GFDL-ESM2G	r1i1p1	1861-01	2005-12	1740	2006-01	2100-12	1140
103	GFDL-ESM2M	r1i1p1	1861-01	2005-12	1740	2006-01	2100-12	1140
104	GISS-E2-H (p1)	r1i1p1	1850-01	2005-12	1872	2006-01	2300-12	3540
105	GISS-E2-H (p3)	r1i1p3	1850-01	2005-12	1872	2006-01	2300-12	3540
106	GISS-E2-R (p1)	r1i1p1	1850-01	2005-12	1872	2006-01	2300-12	3540
107	GISS-E2-R (p2)	r1i1p2	1850-01	2005-12	1872	2006-01	2300-12	3540
108	GISS-E2-R (p3)	r1i1p3	1850-01	2005-12	1872	2006-01	2300-12	3540
109	HadGEM2-CC	r1i1p1	1859-12	2005-11	1752	2005-12	2099-12	1129
110-111	HadGEM2-CC	r2i1p1–r3i1p1	1959-12	2005-12	553	2005-12	2099-12	1129
112	HadGEM2-ES	r1i1p1	1859-12	2005-11	1752	2005-12	2299-12	3529
113	HadGEM2-ES	r2i1p1	1859-12	2005-12	1753	2005-12	2100-11	1140
114	MIROC5	r1i1p1	1850-01	2012-12	1956	2006-01	2100-12	1140
115	MIROC-ESM-CHEM	r1i1p1	1850-01	2005-12	1872	2006-01	2100-12	1140
116	MIROC-ESM	r1i1p1	1850-01	2005-12	1872	2006-01	2100-12	1140
117	MPI-ESM-LR	r1i1p1	1850-01	2005-12	1872	2006-01	2300-12	3540
118-119	MPI-ESM-LR	r2i1p1–r3i1p1	1850-01	2005-12	1872	2006-01	2100-12	1140
120	MPI-ESM-MR	r1i1p1	1850-01	2005-12	1872	2006-01	2100-12	1140
121	MRI-CGCM3	r1i1p1	1850-01	2005-12	1872	2006-01	2100-12	1140
122	NorESM1-M	r1i1p1	1850-01	2005-12	1872	2006-01	2100-12	1140
123	NorESM1-ME	r1i1p1	1850-01	2005-12	1872	2006-01	2100-12	1140

TABLE 2: Start dates, end dates, and lengths (N_m, in months) of the 36 CMIP5 pre-industrial control runs used in this study. EM is the "ensemble member" identifier (see http://cmip-pcmdi.llnl.gov/cmip5/documents.html for further details).

	Model	EM	Start	End	N_m
1	ACCESS1.0	r1i1p1	300-01	799-12	6000
2	ACCESS1.3	r1i1p1	250-01	749-12	6000
3	BCC-CSM1.1	r1i1p1	1-01	500-12	6000
4	BCC-CSM1.1(m)	r1i1p1	1-01	400-12	4800
5	CanESM2	r1i1p1	2015-01	3010-12	11952
6	CCSM4	r1i1p1	800-01	1300-12	6012
7	CESM-BGC	r1i1p1	101-01	600-12	6000
8	CESM-CAM5	r1i1p1	1-01	319-12	3828
9	CMCC-CESM	r1i1p1	4324-01	4600-12	3324
10	CMCC-CM	r1i1p1	1550-01	1879-12	3960
11	CMCC-CMS	r1i1p1	3684-01	4183-12	6000
12	CSIRO-Mk3.6.0	r1i1p1	1651-01	2150-12	6000
13	FGOALS-g2	r1i1p1	201-01	900-12	8400
14	FIO-ESM	r1i1p1	401-01	1200-12	9600
15	GFDL-CM3	r1i1p1	1-01	500-12	6000
16	GFDL-ESM2G	r1i1p1	1-01	500-12	6000
17	GFDL-ESM2M	r1i1p1	1-01	500-12	6000
18	GISS-E2-H (p1)	r1i1p1	2410-01	2949-12	6480
19	GISS-E2-H (p2)	r1i1p2	2490-01	3020-12	6372
20	GISS-E2-H (p3)	r1i1p3	2490-01	3020-12	6372
21	GISS-E2-R (p1)	r1i1p1	3981-01	4530-12	6600
22	GISS-E2-R (p2)	r1i1p2	3590-01	4120-12	6372
23	HadGEM2-CC	r1i1p1	1859-12	2099-12	2881
24	HadGEM2-ES	r1i1p1	1859-12	2435-11	6912
25	INM-CM4	r1i1p1	1850-01	2349-12	6000
26	IPSL-CM5A-LR	r1i1p1	1800-01	2799-12	12000
27	IPSL-CM5A-MR§	r1i1p1	1800-01	2068-12	3228
28	IPSL-CM5B-LR	r1i1p1	1830-01	2129-12	3600
29	MIROC5	r1i1p1	2000-01	2669-12	8040
30	MIROC-ESM-CHEM	r1i1p1	1846-01	2100-12	3060
31	MIROC-ESM	r1i1p1	1800-01	2330-12	6372
32	MPI-ESM-LR	r1i1p1	1850-01	2849-12	12000
33	MPI-ESM-MR	r1i1p1	1850-01	2849-12	12000
34	MRI-CGCM3	r1i1p1	1851-01	2350-12	6000
35	NorESM1-M	r1i1p1	700-01	1200-12	6012
36	NorESM1-ME	r1i1p1	901-01	1152-12	3024

§The IPSL-CM5A-MR control run has a large discontinuity in year 2069. We therefore truncated its control run after December 2068.

TABLE 3: Basic information relating to the start dates, end dates, and lengths (N_m, in months) of the 166 CMIP6 historical and SSP5 simulations used in this study[§]. EM is the "ensemble member" identifier[*].

Model		EM	Hist. Start	Hist. End	Hist. N_m	SSP5 Start	SSP5 End	SSP5 N_m
1-3	ACCESS-CM2	r1i1p1f1–r3i1p1f1	1850-01	2014-12	1980	2015-01	2100-12	1032
4-6	ACCESS-ESM1.5	r1i1p1f1–r3i1p1f1	1850-01	2014-12	1980	2015-01	2100-12	1032
7-31	CanESM5	r1i1p1f1-r25i1p1f1	1850-01	2014-12	1980	2015-01	2100-12	1032
32-56	CanESM5	r1i1p1f2-r25i1p1f2	1850-01	2014-12	1980	2015-01	2100-12	1032
57-61	CESM2	r1i1p1f1, r2i1p1f1	1850-01	2014-12	1980	2015-01	2100-12	1032
	CESM2	r4i1p1f1, r10i1p1f1	1850-01	2014-12	1980	2015-01	2100-12	1032
	CESM2	r11i1p1f1	1850-01	2014-12	1980	2015-01	2100-12	1032
63	CIESM	r1i1p1f1	1850-01	2014-12	1980	2015-01	2100-12	1032
64-69	CNRM-CM6.1	r1i1p1f2–r6i1p1f2	1850-01	2014-12	1980	2015-01	2100-12	1032
70-75	EC-Earth3	r1i1p1f1, r4i1p1f1	1850-01	2014-12	1980	2015-01	2100-12	1032
	EC-Earth3	r6i1p1f1, r11i1p1f1	1850-01	2014-12	1980	2015-01	2100-12	1032
	EC-Earth3	r13i1p1f1, r15i1p1f1	1850-01	2014-12	1980	2015-01	2100-12	1032
76-79	EC-Earth3-Veg	r1i1p1f1–r4i1p1f1	1850-01	2014-12	1980	2015-01	2100-12	1032
80	EC-Earth3-Veg	r6i1p1f1	1850-01	2014-12	1980	2015-01	2100-12	1032
81	GFDL-CM4	r1i1p1f1	1850-01	2014-12	1980	2015-01	2100-12	1032
82	GFDL-ESM4	r1i1p1f1	1850-01	2014-12	1980	2015-01	2100-12	1032
83-85	HadGEM3-GC31-LL	r1i1p1f3–r3i1p1f3	1850-01	2014-12	1980	2015-01	2100-12	1032
86-88	HadGEM3-GC31-MM	r1i1p1f3–r3i1p1f3	1850-01	2014-12	1980	2015-01	2100-12	1032
89	IPSL-CM6A-LR	r1i1p1f1	1950-01	2014-12	780	2015-01	2300-12	3432
90	IPSL-CM6A-LR	r2i1p1f1	1950-01	2014-12	780	2015-01	2100-12	1032
91-92	IPSL-CM6A-LR	r3i1p1f1, r4i1p1f1	1950-01	2014-12	780	2015-01	2054-12	480
93-94	IPSL-CM6A-LR	r6i1p1f1, r14i1p1f1	1950-01	2014-12	780	2015-01	2100-12	1032
95-144	MIROC6	r1i1p1f1–r50i1p1f1	1850-01	2014-12	1980	2015-01	2100-12	1032
145	MIROC-ES2L	r1i1p1f2	1850-01	2014-12	1980	2015-01	2100-12	1032
146-147	MPI-ESM-1.2-HR	r1i1p1f1, r2i1p1f1	1850-01	2014-12	1980	2015-01	2100-12	1032
148-157	MPI-ESM-1.2-LR	r1i1p1f1–r10i1p1f1	1850-01	2014-12	1980	2015-01	2100-12	1032
158	MRI-ESM2.0	r1i1p1f1	1850-01	2014-12	1980	2015-01	2300-12	3432
159-160	NESM3	r1i1p1f1, r2i1p1f1	1850-01	2014-12	1980	2015-01	2100-12	1032
161	NorESM2-MM	r1i1p1f1	1850-01	2014-12	1980	2015-01	2100-12	1032
162-165	UKESM1.0-LL	r1i1p1f2–r4i1p1f2	1850-01	2014-12	1980	2015-01	2100-12	1032
166	UKESM1.0-LL	r8i1p1f2	1850-01	2014-12	1980	2015-01	2100-12	1032

[§] CMIP6 model acronyms are from: https://pcmdi.llnl.gov/CMIP6/ArchiveStatistics/esgf_data_holdings/

[*] See: https://docs.google.com/document/d/1h0r8RZr_f3-8egBMMh7aqLwy3snpD6_MrDz1q8n5XUk/edit

TABLE 4: Start dates, end dates, and lengths (N_m, in months) of the 30 CMIP6 pre-industrial control runs used in this study.[§] EM is the "ensemble member" identifier.[*]

	Model	EM	Start	End	N_m
1	ACCESS-CM2	r1i1p1f1	950-01	1449-12	6000
2	ACCESS-ESM1.5	r1i1p1f1	101-01	1000-12	10800
3	CESM2	r1i1p1f1	1-01	1200-12	14400
4	CESM2-FV2	r1i1p1f1	1-01	500-12	6000
5	CESM2-WACCM	r1i1p1f1	1-01	499-12	5988
6	CESM2-WACCM-FV	r1i1p1f1	1-01	500-12	6000
7	CNRM-CM6.1-HR	r1i1p1f2	1850-01	2149-12	3600
8	CNRM-ESM2.1	r1i1p1f2	1850-01	2105-12	3072
9	E3SM-1.0	r1i1p1f1	1-01	500-12	6000
10	E3SM-1.1	r1i1p1f1	1850-01	2014-12	1980
11	E3SM-1.1-ECA	r1i1p1f1	1850-01	2014-12	1980
12	EC-Earth3	r1i1p1f1	2259-01	2759-12	6012
13	EC-Earth3-Veg	r1i1p1f1	1850-01	2349-12	6000
14	GFDL-CM4	r1i1p1f1	151-01	650-12	6000
15	GFDL-ESM4	r1i1p1f1	1-01	500-12	6000
16	HadGEM3-GC31-LL	r1i1p1f1	1850-01	2349-12	6000
17	INM-CM4.8	r1i1p1f1	1850-01	2380-12	6372
18	INM-CM5.0	r1i1p1f1	1996-01	3196-12	14412
19	IPSL-CM6A-LR	r1i1p1f1	1850-01	3049-12	14400
20	MIROC6	r1i1p1f1	3200-01	3999-12	9600
21	MIROC-ES2L	r1i1p1f2	1850-01	2349-12	6000
22	MPI-ESM-1.2-HAM	r1i1p1f1	1850-01	2629-12	9360
23	MPI-ESM-1.2-HR	r1i1p1f1	1850-01	2349-12	6000
24	MPI-ESM-1.2-LR	r1i1p1f1	1850-01	2849-12	12000
25	MRI-ESM2.0	r1i1p1f1	1850-01	2550-12	8412
26	NorCPM1	r1i1p1f1	1-01	500-12	6000
27	NorESM2-LM	r1i1p1f1	1600-01	2100-12	6012
28	NorESM2-MM	r1i1p1f1	1200-01	1699-12	6000
29	SAM0-UNICON	r1i1p1f1	1-01	700-12	8400
30	UKESM1.0-LL	r1i1p1f2	1960-01	2709-12	9000

[§] CMIP6 model acronyms are from: https://pcmdi.llnl.gov/CMIP6/ArchiveStatistics/esgf_data_holdings/

[*] See: https://docs.google.com/document/d/1h0r8RZr_f3-8egBMMh7aqLwy3snpD6_MrDz1q8n5XUk/edit