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# Celebrating the anniversary of three key events in climate change science

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# Supplementary Information for:
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## 1 Satellite atmospheric temperature data

In calculating the signal detection times shown in Figure 1, we used satellite estimates of atmospheric temperature produced by Remote Sensing Systems[1,2], the Center for Satellite Applications and Research[3,4], and the University of Alabama at Huntsville[5,6]. We refer to these groups subsequently as RSS, STAR, and UAH (respectively). All three groups provide satellite measurements of the temperatures of the mid- to upper troposphere (TMT) and the lower stratosphere (TLS). Our focus here is on estimating the detection time for an anthropogenic fingerprint in satellite TMT data. TLS is required for correcting TMT for the influence it receives from stratospheric cooling[7] (see Section 3).

Satellite datasets are in the form of monthly means on $2.5^\circ \times 2.5^\circ$ latitude/longitude grids. At the time this analysis was performed, temperature data were available for the 480-month period from January 1979 to December 2018. We used the most recent dataset versions from each group: 4.0 (RSS), 4.1 (STAR), and 6.0 (UAH).

Studies of the size, patterns, and causes of atmospheric temperature changes have also relied on information from radiosondes[8,9,10,11,12]. Non-climatic factors, such as refinements over time in radiosonde instrumentation and thermal shielding, hamper the identification of true climate changes[8,13]. Additionally, radiosonde data have much sparser coverage than satellite data, particularly in the Southern Hemisphere. The spatially complete coverage of MSU and AMSU offers advantages for obtaining reliable estimates of hemispheric- and global-scale temperature trends and patterns of temperature change.

## 2 Details of model output

We used model output from phase 5 of CMIP, the Coupled Model Intercomparison Project[14]. The simulations analyzed here were contributed by 19 different research groups (see Supplementary Table S1). Our focus was on three different types of numerical experiment: 1) simulations with estimated historical changes in human and natural external forcings; 2) integrations with 21st century changes in greenhouse gases and anthropogenic aerosols prescribed according to the Representative Concentration Pathway 8.5 (RCP8.5), with radiative forcing of approximately 8.5 W/m$^2$ in 2100, eventually stabilizing at roughly 12 W/m$^2$; and 3) pre-industrial control runs with no changes in external influences on climate. Details of these simulations are provided in Supplementary Tables S2 and S3.

Most CMIP5 historical simulations end in December 2005. RCP8.5 simulations were typically initiated from conditions of the climate system at the end of the historical run. To avoid truncating comparisons between modeled and observed temperature trends in December 2005, we spliced together synthetic satellite temperatures from the historical simulations and the RCP8.5 runs. Splicing allows us to compare actual and synthetic temperature changes over the full 40-year length of the satellite record. The acronym “HIST+8.5” identifies these spliced simulations.

## 3 Method used for correcting TMT data

Trends in TMT estimated from microwave sounders receive a substantial contribution from the cooling of the lower stratosphere[7,15,16,17]. In Fu et al. (2004), a regression-based method was developed for removing the bulk of this stratospheric cooling component of TMT[7]. This method has been validated with both observed and model atmospheric temperature data[15,18,19]. Here, we refer to the corrected version of TMT as $\text{TMT}_{cr}$. The main text discusses corrected TMT only, and does not use the subscript $cr$ to identify corrected TMT.

For calculating tropical averages of $\text{TMT}_{cr}$, Fu et al. (2005)[16] used:

$$\text{TMT}_{cr} = a_{24}\text{TMT} + (1 - a_{24})\text{TLS} \tag{1}$$

where $a_{24} = 1.1$. For the global domain considered here, lower stratospheric cooling makes a larger contribution to TMT trends, so $a_{24}$ is larger[7,17]. In Fu et al (2004)[7] and Johanson and Fu (2006)[17], $a_{24} \approx 1.15$ was applied directly to near-global averages of TMT and TLS. Since we are performing corrections on local (grid-point) data, we used $a_{24} = 1.1$ between $30°$N and $30°$S, and $a_{24} = 1.2$ poleward of $30°$. All results in the main text rely on this correction approach, which is approximately equivalent to use of the $a_{24} = 1.15$ for globally-averaged data. Use of a more conservative approach (assuming $a_{24} = 1.1$ at all latitudes) yields smaller tropospheric warming, but the model-predicted HIST+8.5 fingerprint is still identifiable at a stipulated $5\sigma$ threshold in all three satellite $\text{TMT}_{cr}$ datasets.

## 4 Calculation of synthetic satellite temperatures

We use a local weighting function method developed at RSS to calculate synthetic satellite temperatures from model output[20]. At each model grid-point, simulated temperature profiles were convolved with local weighting functions. The weights depend on the grid-point surface pressure, the surface type (land or ocean), and the selected layer-average temperature (TLS or TMT).

## 5 Fingerprint method

Detection methods generally require an estimate of the true but unknown climate-change signal in response to an individual forcing or set of forcings[21,22,23,24,25,26]. This is often referred to as the fingerprint $F(x)$.

We define $F(x)$ as follows. Let $S(i, j, x, t)$ represent annual-mean synthetic MSU temperature data at grid-point $x$ and year $t$ from the $i^{th}$ realization of the $j^{th}$ model's HIST+8.5 simulation, where:

$i = 1, \dots N_r(j)$ (the number of realizations for the $j^{th}$ model).

$j = 1, \dots N_m$ (the number of models used in fingerprint estimation).

$x = 1, \dots N_x$ (the total number of grid-points).

$t = 1, \dots N_t$ (the time in years).

Here, $N_r$ ranges from 1 to 5 realizations and $N_m = 37$ models. After transforming synthetic MSU temperature data from each model's native grid to a common $10° \times 10°$ latitude/longitude grid, $N_x = 576$ grid-points for corrected TMT. The fingerprint is estimated over the full satellite era (1979 to 2018), so $N_t$ is 40 years. Because the RSS TMT data do not have coverage poleward of $82.5°$, the latitudinal extent of the regridded data is from $80°$N to $80°$S. This is the minimum common coverage in the three satellite datasets.

The multi-model average atmospheric temperature change, $\overline{\overline{S}}(x,t)$, was calculated by first averaging over an individual model's HIST+8.5 realizations (where multiple realizations were available), and then averaging over models. The double overbar denotes these two averaging steps. Anomalies were then defined at each grid-point $x$ and year $t$ with respect to the local climatological annual mean. The fingerprint is the first Empirical Orthogonal Function (EOF) of the anomalies of $\overline{\overline{S}}(x,t)$.

We seek to determine whether the pattern similarity between the time-varying observations and $F(x)$ shows a statistically significant increase over time. To address this question, we require control run estimates of internally generated variability in which we know *a priori* that there is no expression of the fingerprint (except by chance).

We obtain these variability estimates from control runs performed with multiple models. Because the length of the 36 control runs analyzed here varies by a factor of up to 4, models with longer control integrations could have a disproportionately large impact on our noise estimates. To guard against this possibility, the noise estimates rely on the last

200 years of each model's pre-industrial control run, yielding 7,200 years of concatenated control run data. Use of the last 200 years reduces the contribution of any initial residual drift to noise estimates.

Synthetic TMT data from individual model control runs are regridded to the same $10^\circ \times 10^\circ$ target grid used for fingerprint estimation. After regridding, anomalies are defined relative to the local climatological annual means calculated over the full length of each control run. Since control run drift can bias S/N estimates, its removal is advisable. We assume here that drift can be well-approximated by a least-squares linear trend at each grid-point. Trend removal is performed over the last 200 years of each control run (since only the last 200 years are concatenated).

Observed annual-mean TMT data are first transformed to the $10^\circ \times 10^\circ$ latitude/longitude grid used for the model HIST+8.5 simulations and control runs, and are then expressed as anomalies relative to climatological annual means over 1979 to 2018. The observed temperature data are projected onto $F(x)$, the time-invariant fingerprint:

$$Z_o(t) = \sum_{x=1}^{N_x} O(x,t)\, F(x) \quad t = 1, 2, \ldots, 40 \tag{2}$$

where $O(x,t)$ denotes the observed annual-mean TMT data. This projection is equivalent to a spatially uncentered covariance between the patterns $O(x,t)$ and $F(x)$ at year $t$. The signal time series $Z_o(t)$ provides information on the fingerprint strength in the observations.

If observed patterns of temperature change are becoming increasingly similar to $F(x)$, $Z_o(t)$ should increase over time. A recent publication[27] provides figures showing both $F(x)$ and the observed patterns of annual-mean trends in TMT.

Hasselmann's 1979 paper discusses the rotation of $F(x)$ in a direction that maximizes the signal strength relative to the control run noise[21]. Optimization of $F(x)$ generally leads to enhanced detectability of the signal[28,29]. In all cases we considered, we achieved detection of an externally-forced fingerprint in satellite TMT data without any optimization of $F(x)$. We therefore show only non-optimized results in our Figure 1.

All model and observational temperature data used in the fingerprint analysis are appropriately area-weighted. Weighting involves multiplication by the square root of the cosine of the grid node's latitude[30].

## 6 Estimating detection time

We assess the significance of changes in $Z_o(t)$ by comparing trends in $Z_o(t)$ with a null distribution of trends. To generate this null distribution, we require a case in which $O(x, t)$ is replaced by a record in which we know *a priori* that there is no expression of the fingerprint, except by chance. Here we replace $O(x, t)$ by the concatenated noise data set $C(x, t)$ after first regridding and removing residual drift from $C(x, t)$ (see above). The noise time series $N_c(t)$ is the projection of $C(x, t)$ onto the fingerprint:

$$N_c(t) = \sum_{x=1}^{N_x} C(x,t)\, F(x) \quad t = 1, \ldots, 7200 \tag{3}$$

Our detection time $T_d$ is based on the signal-to-noise ratio, S/N. As in our previous work[27], we calculate S/N ratios by fitting least-squares linear trends of increasing length $L$ years to $Z_o(t)$, and then comparing these with the standard deviation of the distribution of non-overlapping $L$-length trends in $N_c(t)$. The numerator of the S/N ratio measures the trend in the pattern agreement between the model-predicted "human influence" fingerprint and observations; the denominator measures the trend in agreement between the fingerprint and patterns of natural climate variability. Detection occurs after $L_d$ years, when the S/N ratio first exceeds some stipulated signal detection threshold, and then remains continuously above that threshold for all values of $L > L_d$. For example, $L_d = 10$ would signify that $T_d = 1988$ – *i.e.*, that detection of a human-caused tropospheric warming fingerprint occurred in 1988, 10 years after the start of the satellite temperature record.

We estimated $T_d$ with both $3\sigma$ and $5\sigma$ signal detection thresholds. The more stringent $5\sigma$ threshold is often employed in particle physics (as in the discovery of the Higgs boson). For detection at a $3\sigma$ threshold, there is a chance of roughly one in 741 that the "match" between the model-predicted anthropogenic fingerprint and the observed patterns of tropospheric temperature change could actually be due to natural internal variability (as represented by the 36 models analyzed here). With a $5\sigma$ detection threshold, this complementary cumulative probability decreases to roughly one in 3.5 million*.

We make three assumptions in order to calculate $T_d$. First, we assume that our knowledge of observed tropospheric temperature change is derived from the latest MSU and AMSU dataset versions produced by RSS, UAH, and STAR. Second, we assume that large ensembles of forced and unforced simulations performed with state-of-the-art climate models provide the best current estimates of a human fingerprint and natural internal climate variability. Third, we assume that although the strength of the fingerprint in the observations changes over time, the fingerprint pattern itself is relatively stable – an assumption that is justifiable for TMT[27].

Our assumption regarding the adequacy of model variability estimates is critical. Observed temperature records are simultaneously influenced by both internal variability and multiple external forcings. We do not observe "pure" internal variability, so there will always be some irreducible uncertainty in partitioning observed temperature records into internally generated and externally forced components. All model-versus-observed variability comparisons are affected by this uncertainty, particularly on less well-observed multi-decadal timescales.

The model-data variability comparisons that have been performed, both for surface

*Probabilities are based on a one-tailed test. A one-tailed test is appropriate here, since we seek to determine whether natural variability could yield larger time-increasing similarity with the fingerprint pattern than the similarity we obtained by comparing the fingerprint with the satellite data.

temperature[22,28,31,32,33] and tropospheric temperature[27,34] indicate that current climate models do not systematically underestimate the amplitude of observed decadal-timescale temperature variability. For tropospheric temperature, the converse is the case – on average, CMIP3 and CMIP5 models appear to slightly overestimate the amplitude of observed temperature variability on 5 to 20-year timescales[27,34]. While we cannot definitively rule out a significant deficit in the amplitude of simulated TMT variability on longer 30-to 40-year timescales, the observed TMT variability on these timescales would have to be underestimated by a factor of 2 or more in order to negate the positive fingerprint identification results obtained here for a $3\sigma$ detection threshold.

## 7 Detection time results

At the $3\sigma$ threshold, $T_d$ =1998 for RSS and STAR and 2002 for UAH (Figure 1). This means that $L_d$ is 20 years for RSS and STAR and 24 years for UAH. With a more stringent $5\sigma$ threshold the detection time is longer: $T_d$ =2003 for STAR, 2005 for RSS, and 2016 for UAH, yielding $L_d$ values of 25, 27, and 38 years, respectively. The UAH results are noteworthy. Even though UAH tropospheric temperature data have consistently shown less warming than other datasets[7,35,36,37], UAH still yields confident $5\sigma$ detection of an anthropogenic fingerprint.

## 8 Use of HIST+8.5 runs for fingerprint estimation

Our S/N analysis relies on the fingerprint estimated from the HIST+8.5 runs. We also use the fingerprint estimated from CMIP5 simulations with anthropogenic forcing only (ANTHRO). Over the full 40-year satellite record, anthropogenic forcing is substantially larger than natural external forcing. This explains why the ANTHRO and HIST+8.5 fingerprint patterns are very similar. This similarity primarily reflects the large tropospheric warming in response to human-caused changes in well-mixed greenhouse gases[20].

We focus on the HIST+8.5 fingerprint for two reasons. The first reason is related to ensemble size. Only 8 models were available for estimating the ANTHRO fingerprint, while the HIST+8.5 fingerprint was based on results from 49 HIST+8.5 realizations performed with 37 models. We expect, therefore, that ANTHRO yields noisier estimates of the climate response to external forcing. Second, the ANTHRO simulations end in 2005, and (unlike HIST+8.5 runs) cannot be spliced with RCP8.5 results. This means that ANTHRO tropospheric temperatures cannot be compared with observations over the full satellite record.

The choice of HIST+8.5 or ANTHRO fingerprints has minimal influence on the detection times estimated here. Both fingerprints are detectable with high confidence in all three satellite data sets. The similarity of the S/N results obtained with the HIST+8.5 and ANTHRO fingerprints confirms that observed tropospheric temperature changes are primarily attributable to anthropogenic forcing.

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## Supplementary Tables

Supplementary Table S1: CMIP5 models used in this study.

| | Model | Country | Modeling center |
|---|---|---|---|
| 1 | ACCESS1.0 | Australia | Commonwealth Scientific and Industrial Research Organization and Bureau of Meteorology |
| 2 | ACCESS1.3 | Australia | Commonwealth Scientific and Industrial Research Organization and Bureau of Meteorology |
| 3 | BCC-CSM1.1 | China | Beijing Climate Center, China Meteorological Administration |
| 4 | BCC-CSM1.1(m) | China | Beijing Climate Center, China Meteorological Administration |
| 5 | CanESM2 | Canada | Canadian Centre for Climate Modelling and Analysis |
| 6 | CCSM4 | USA | National Center for Atmospheric Research |
| 7 | CESM1-BGC | USA | National Science Foundation, U.S. Dept. of Energy, National Center for Atmospheric Research |
| 8 | CESM1-CAM5 | USA | National Science Foundation, U.S. Dept. of Energy, National Center for Atmospheric Research |
| 9 | CMCC-CESM | Italy | Centro Euro-Mediterraneo per I Cambiamenti Climatici |
| 10 | CMCC-CM | Italy | Centro Euro-Mediterraneo per I Cambiamenti Climatici |
| 11 | CMCC-CMS | Italy | Centro Euro-Mediterraneo per I Cambiamenti Climatici |
| 12 | CSIRO-Mk3.6.0 | Australia | Commonwealth Scientific and Industrial Research Organization in collaboration with Queensland Climate Change Centre of Excellence |
| 13 | EC-EARTH | Various | EC-EARTH consortium |
| 14 | FGOALS-g2 | China | LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences; and CESS, Tsinghua University |
| 15 | FIO-ESM | China | The First Institute of Oceanography, SOA |
| 16 | GFDL-CM3 | USA | NOAA Geophysical Fluid Dynamics Laboratory |

Supplementary Table S1: CMIP5 models used in this study (continued).

| | Model | Country | Modeling center |
|---|---|---|---|
| 17 | GFDL-ESM2G | USA | NOAA Geophysical Fluid Dynamics Laboratory |
| 18 | GFDL-ESM2M | USA | NOAA Geophysical Fluid Dynamics Laboratory |
| 19 | GISS-E2-H (p1) | USA | NASA Goddard Institute for Space Studies |
| 20 | GISS-E2-H (p2) | USA | NASA Goddard Institute for Space Studies |
| 21 | GISS-E2-H (p3) | USA | NASA Goddard Institute for Space Studies |
| 22 | GISS-E2-R (p1) | USA | NASA Goddard Institute for Space Studies |
| 23 | GISS-E2-R (p2) | USA | NASA Goddard Institute for Space Studies |
| 24 | GISS-E2-R (p3) | USA | NASA Goddard Institute for Space Studies |
| 25 | HadGEM2-CC | UK | Met. Office Hadley Centre |
| 26 | HadGEM2-ES | UK | Met. Office Hadley Centre |
| 27 | INM-CM4 | Russia | Institute for Numerical Mathematics |
| 28 | IPSL-CM5A-LR | France | Institut Pierre-Simon Laplace |
| 29 | IPSL-CM5A-MR | France | Institut Pierre-Simon Laplace |
| 30 | IPSL-CM5B-LR | France | Institut Pierre-Simon Laplace |
| 31 | MIROC5 | Japan | Atmosphere and Ocean Research Institute (the University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology |
| 32 | MIROC-ESM-CHEM | Japan | As for MIROC5 |
| 33 | MIROC-ESM | Japan | As for MIROC5 |
| 34 | MPI-ESM-LR | Germany | Max Planck Institute for Meteorology |

Supplementary Table S1: CMIP5 models used in this study (continued).

| | Model | Country | Modeling center |
|---|---|---|---|
| 35 | MPI-ESM-MR | Germany | Max Planck Institute for Meteorology |
| 36 | MRI-CGCM3 | Japan | Meteorological Research Institute |
| 37 | NorESM1-M | Norway | Norwegian Climate Centre |
| 38 | NorESM1-ME | Norway | Norwegian Climate Centre |

Supplementary Table S2: Basic information relating to the start dates, end dates, and lengths ($N_m$, in months) of the 37 CMIP5 historical and RCP8.5 simulations used in this study. EM is the "ensemble member" identifier*.

| | 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 | CanESM2 | r1i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2100-12 | 1140 |
| 6 | CanESM2 | r2i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2100-12 | 1140 |
| 7 | CanESM2 | r3i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2100-12 | 1140 |
| 8 | CanESM2 | r4i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2100-12 | 1140 |
| 9 | CanESM2 | r5i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2100-12 | 1140 |
| 10 | CCSM4 | r1i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2100-12 | 1140 |
| 11 | CCSM4 | r2i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2100-12 | 1140 |
| 12 | CCSM4 | r3i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2100-12 | 1140 |
| 13 | CESM1-BGC | r1i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2100-12 | 1140 |
| 14 | CESM1-CAM5 | r1i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2100-12 | 1140 |
| 15 | CMCC-CESM | r1i1p1 | 1850-01 | 2005-12 | 1872 | 2000-01 | 2095-12 | 1140 |
| 16 | CMCC-CM | r1i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2100-12 | 1140 |
| 17 | CMCC-CMS | r1i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2100-12 | 1140 |
| 18 | CSIRO-Mk3.6.0 | r10i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2100-12 | 1140 |
| 19 | EC-EARTH | r8i1p1 | 1850-01 | 2012-12 | 1956 | 2006-01 | 2100-12 | 1140 |
| 20 | FGOALS-g2 | r1i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2101-12 | 1152 |
| 21 | FIO-ESM | r1i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2100-12 | 1140 |
| 22 | GFDL-CM3 | r1i1p1 | 1860-01 | 2005-12 | 1752 | 2006-01 | 2100-12 | 1140 |
| 23 | GFDL-ESM2G | r1i1p1 | 1861-01 | 2005-12 | 1740 | 2006-01 | 2100-12 | 1140 |
| 24 | GFDL-ESM2M | r1i1p1 | 1861-01 | 2005-12 | 1740 | 2006-01 | 2100-12 | 1140 |

Supplementary Table S2 (continued): Information on the 37 CMIP5 historical and RCP8.5 simulations used in this study.

| Model | EM | Hist. Start | Hist. End | Hist. (months) | RCP8.5 Start | RCP8.5 End | RCP8.5 (months) |
|---|---|---|---|---|---|---|---|
| 25 GISS-E2-H (p1) | r1i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2300-12 | 3540 |
| 26 GISS-E2-H (p3) | r1i1p3 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2300-12 | 3540 |
| 27 GISS-E2-R (p1) | r1i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2300-12 | 3540 |
| 28 GISS-E2-R (p2) | r1i1p2 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2300-12 | 3540 |
| 29 GISS-E2-R (p3) | r1i1p3 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2300-12 | 3540 |
| 30 HadGEM2-CC | r1i1p1 | 1859-12 | 2005-11 | 1752 | 2005-12 | 2099-12 | 1129 |
| 31 HadGEM2-CC | r2i1p1 | 1959-12 | 2005-12 | 553 | 2005-12 | 2099-12 | 1129 |
| 32 HadGEM2-CC | r3i1p1 | 1959-12 | 2005-12 | 553 | 2005-12 | 2099-12 | 1129 |
| 33 HadGEM2-ES | r1i1p1 | 1859-12 | 2005-11 | 1752 | 2005-12 | 2299-12 | 3529 |
| 34 HadGEM2-ES | r2i1p1 | 1859-12 | 2005-12 | 1753 | 2005-12 | 2100-11 | 1140 |
| 35 INM-CM4 | r1i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2100-12 | 1140 |
| 36 IPSL-CM5A-LR | r1i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2300-12 | 3540 |
| 37 IPSL-CM5A-LR | r2i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2100-12 | 1140 |
| 38 IPSL-CM5A-MR | r1i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2100-12 | 1140 |
| 39 IPSL-CM5B-LR | r1i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2100-12 | 1140 |
| 40 MIROC5 | r1i1p1 | 1850-01 | 2012-12 | 1956 | 2006-01 | 2100-12 | 1140 |
| 41 MIROC-ESM-CHEM | r1i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2100-12 | 1140 |
| 42 MIROC-ESM | r1i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2100-12 | 1140 |
| 43 MPI-ESM-LR | r1i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2300-12 | 3540 |
| 44 MPI-ESM-LR | r2i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2100-12 | 1140 |
| 45 MPI-ESM-LR | r3i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2100-12 | 1140 |
| 46 MPI-ESM-MR | r1i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2100-12 | 1140 |
| 47 MRI-CGCM3 | r1i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2100-12 | 1140 |
| 48 NorESM1-M | r1i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2100-12 | 1140 |
| 49 NorESM1-ME | r1i1p1 | 1850-01 | 2005-12 | 1872 | 2006-01 | 2100-12 | 1140 |

[*] See http://cmip-pcmdi.llnl.gov/cmip5/documents.html for further details.

Supplementary Table S3: 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.*

| | 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 |

Supplementary Table S3 (continued): Information on the 36 CMIP5 pre-industrial control runs used in this study.

| | Model | EM | Start | End | $N_m$ |
|---|---|---|---|---|---|
| 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 |

[*] See http://cmip-pcmdi.llnl.gov/cmip5/documents.html for further details.

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