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1 **Celebrating the Anniversary of Three Key Events in**
2 **Climate Change Science**

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17 **Climate science celebrates three 40th anniversaries in 2019: release of the Charney**
18 **report, publication of a key paper on anthropogenic signal detection, and the start of**
19 **satellite temperature measurements. This confluence of scientific understanding and**
20 **data led to the identification of a human fingerprint in atmospheric temperature.**

21 We discuss below the events commemorated by these anniversaries. Our focus is on
22 understanding how the scientific advances arising from these events aided efforts to identify
23 human influences on the thermal structure of the atmosphere.

24 **The Charney report**

25 In 1979, the U.S. National Academy of Sciences published the findings of an “Ad Hoc
26 Study Group on Carbon Dioxide and Climate”. This is frequently referred to as the Char-
27 ney report¹. The authors did not have many of the scientific advantages available today:
28 international climate science assessments based on thousands of relevant peer-reviewed sci-
29 entific papers^{2,3,4}, four decades of satellite measurements of global climate change⁵, land
30 and ocean surface temperature datasets spanning more than 120 years⁶, estimates of natu-
31 ral climate variability^{7,8}, and sophisticated three-dimensional numerical models of Earth’s
32 climate system. Nevertheless, the report’s principal findings have aged remarkably well.
33 Consider conclusions regarding the equilibrium climate sensitivity (ECS): “*We estimate*
34 *the most probable global warming for a doubling of CO₂ to be near 3°C with a probable*
35 *error of +/- 1.5°C*”. These values are in accord with current understanding⁹ and are now

36 supported by multiple lines of evidence that were unavailable in 1979. Examples include
37 observed patterns of surface warming, greenhouse gas and temperature changes on Ice Age
38 timescales, and results from multi-model ensembles of externally forced simulations^{3,4,9}.

39 There is also better process-level understanding of the feedbacks contributing to ECS
40 uncertainties^{10,11,12}. Charney *et al.* understood that the factor of three spread in ECS was
41 mainly due to uncertainties in the net effect of high and low cloud feedbacks¹³. Reliable
42 assessment of cloud feedbacks required “*comprehensive numerical modeling of the general*
43 *circulations of the atmosphere and the oceans together with validation by comparison of*
44 *the observed with the model-produced cloud types and amounts.*” This conclusion foreshad-
45 owed rigorous evaluation of model cloud properties with satellite data¹⁴. Such comparisons
46 ultimately led to the elucidation of robust cloud responses to greenhouse warming¹⁵, and
47 to the 2013 conclusion of the Intergovernmental Panel on Climate Change (IPCC) that “*the*
48 *sign of the net radiative feedback due to all cloud types is... likely positive*”¹⁰.

49 The ocean’s role in climate change featured prominently in the Charney report. The au-
50 thors noted that ocean heat uptake would delay the emergence of a human-caused warming
51 signal from the background noise of natural variability¹⁶. This delay, they wrote, meant that
52 humanity “*...may not be given a warning until the CO₂ loading is such that an appreciable*
53 *climate change is inevitable*”. The finding that “*On time scales of decades... the coupling*
54 *between the mixed layer and the upper thermocline must be considered*” provided impetus
55 for the development of atmosphere-ocean General Circulation Models (GCMs).

56 The authors also knew that scientific uncertainties did not negate the reality and serious-
57 ness of human-caused climate change: “*We have examined with care all known negative*
58 *feedback mechanisms, such as increase in low or middle cloud amount, and have con-*
59 *cluded that the oversimplifications and inaccuracies in the models are not likely to have*
60 *vitiating the principal conclusion that there will be appreciable warming.*” Although the
61 GCMs available in 1979 were not yet sufficiently reliable for predicting regional changes,
62 Charney *et al.* cautioned that the “*associated regional climate changes so important to the*
63 *assessment of socioeconomic consequences may well be significant*”.

64 In retrospect, the Charney report seems like the scientific equivalent of the handwriting
65 on the wall. Forty years ago, its authors issued a clear warning of the potentially significant
66 socioeconomic consequences of human-caused warming. Their warning was accurate, and
67 remains more relevant than ever.

68 **Hasselmann’s optimal detection paper**

69 The second scientific anniversary marks the publication of a paper by Klaus Hasselmann
70 entitled: “*On the signal-to-noise problem in atmospheric response studies*”¹⁷. This is now
71 widely regarded as the first serious effort to provide a sound statistical framework for iden-
72 tifying a human-caused warming signal.

73 In the 1970s, there was recognition that GCM simulations yielded both “signal” and
74 “noise” when forced by changes in atmospheric CO₂ or other external factors¹⁸. The sig-

75 nal was the climate response to the altered external factor. The noise arose from natural
76 internal climate variability. Noise estimates were obtained from observations or by running
77 an atmospheric GCM coupled to a simple model of the upper ocean. In the presence of
78 intrinsic noise, statistical methods were required to identify areas of the world where first
79 detection of a human-caused warming signal might occur.

80 One key insight in Hasselmann's 1979 paper was that analysts should look at the sta-
81 tistical significance of global geographical patterns of climate change. Previous work had
82 assessed the significance of the local climate response to a particular external forcing at
83 thousands of individual model grid-points. Climate information at these individual loca-
84 tions was correlated in space and in time, hampering assessment of overall significance.
85 Hasselmann noted that "*...it is necessary to regard the signal and noise fields as multi-*
86 *dimensional vector quantities... and the significance analysis should accordingly be car-*
87 *ried out with respect to this multi-variate statistical field, rather than in terms of individual*
88 *gridpoint statistics*". Instead of looking for the needle in a tiny corner of a large haystack
89 (and then proceeding to search the next tiny corner), Hasselmann advocated for a more
90 efficient strategy – searching the entire haystack simultaneously.

91 The paper pointed out that theory, observations, and models provide considerable in-
92 formation about signal and noise properties. For example, changes in solar irradiance, vol-
93 canic aerosols, and greenhouse gases produce signals with different patterns, amplitudes,
94 and frequencies^{2,3,4,8,19}. These unique signal characteristics ("fingerprints") can be used to

95 distinguish climate signals from climate noise.

96 Hasselmann’s paper was a statistical roadmap for hundreds of subsequent climate change
97 detection and attribution (“D&A”) studies. These investigations identified anthropogenic
98 fingerprints in a wide range of independently monitored observational datasets^{2,3,4}. D&A
99 research provided strong scientific support for the conclusion reached by the IPCC in 2013:
100 *“it is extremely likely that human influence has been the dominant cause of the observed*
101 *warming since the mid-20th century”*⁴.

102 **Forty years of satellite temperature data**

103 In November 1978, Microwave Sounding Units (MSUs) on NOAA polar-orbiting satellites
104 began monitoring the microwave emissions from oxygen molecules. These emissions are
105 proportional to the temperature of broad atmospheric layers⁵. A successor to MSU, the
106 Advanced Microwave Sounding Unit (AMSU), was deployed in 1998. Estimates of global
107 changes in atmospheric temperature can be obtained from MSU and AMSU measurements.

108 Over their 40-year history, MSU and AMSU data have been essential ingredients in
109 hundreds of research investigations. These datasets allowed scientists to study the size,
110 significance, and causes of global trends and variability in Earth’s atmospheric temperature
111 and circulation, to quantify the tropospheric cooling after major volcanic eruptions, to eval-
112 uate climate model performance, and to assess the consistency between observed surface
113 and tropospheric temperature changes^{2,3,4,20}.

114 Satellite atmospheric temperature data were also a useful test-bed for Hasselmann's
115 signal detection strategy. They had continuous, near-global coverage⁵. Data products
116 were available from multiple research groups, allowing uncertainties in temperature re-
117 trievals to be quantified. Signal detection studies with MSU and AMSU revealed that
118 human fingerprints were identifiable in the warming of the troposphere and cooling of the
119 lower stratosphere⁸, confirming model projections made over 50 years ago²¹. Tropospheric
120 warming is largely due to increases in atmospheric CO₂ from fossil fuel use^{2,3,4,8,20}, while
121 lower stratospheric cooling over the 40-year satellite record²² is mainly attributable to an-
122 thropogenic depletion of stratospheric ozone²³.

123 While enabling significant scientific advances, MSU and AMSU temperature data have
124 also been at the center of scientific and political imbroglios. Some controversies were re-
125 lated to differences between surface warming inferred from thermometers and tropospheric
126 warming estimated from satellites. Claims that these warming rate differences cast doubt
127 on the reliability of the surface data have not been substantiated^{20,24}. Other disputes focused
128 on how to adjust for non-climatic artifacts arising from orbital decay and drift, instrument
129 calibration drift, and the transition between MSU and AMSU instruments^{5,20}. More re-
130 cently, claims of no significant warming since 1998 have been based on artfully selected
131 subsets of satellite temperature data. Such claims are erroneous and do not call into ques-
132 tion the reality of long-term tropospheric warming²⁵.

133 **A confluence of scientific understanding**

134 The zeitgeist of 1979 was favorable for anthropogenic signal detection. From the Charney
135 report, which relied on basic theory and early climate model simulations, there was clear
136 recognition that fossil fuel burning would yield an appreciable global warming signal¹.
137 Klaus Hasselmann's paper¹⁷ outlined a rational approach for detecting this signal. Satellite-
138 borne microwave sounders began to monitor atmospheric temperature, providing global
139 patterns of multi-decadal climate change and natural internal variability – information re-
140 quired for successful application of Hasselmann's signal detection method.

141 Because of this confluence in scientific understanding, we can now answer the follow-
142 ing question: when did a human-caused tropospheric warming signal first emerge from the
143 background noise of natural climate variability? We addressed this question by applying
144 a fingerprint method related to Hasselmann's approach (see online Methods). An anthro-
145 pogenic fingerprint of tropospheric warming is identifiable with high statistical confidence
146 in all currently available satellite datasets (Figure 1). In two out of three datasets, finger-
147 print detection at a 5-sigma threshold – the gold standard for discoveries in particle physics
148 – occurs no later than 2005, only 27 years after the 1979 start of the satellite measurements.
149 Humanity cannot afford to ignore such clear signals.

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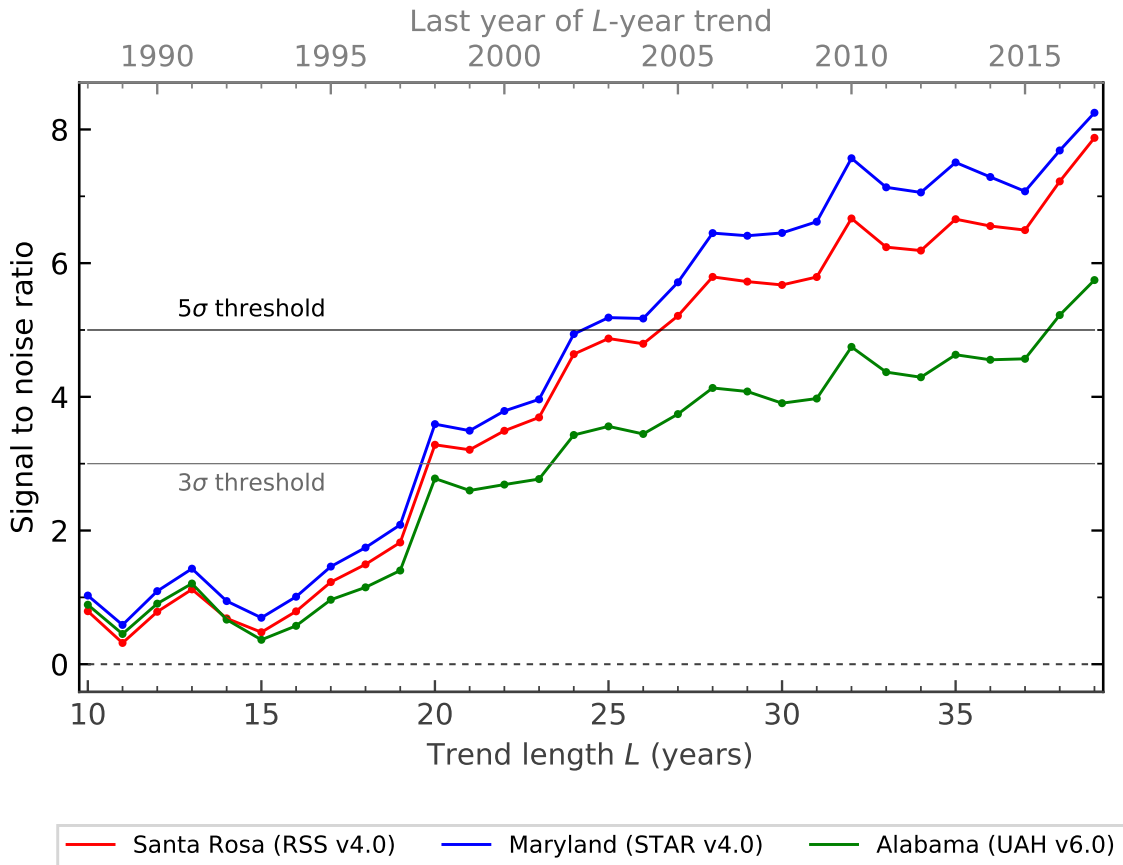


Figure 1: Signal-to-noise ratios (S/N) used for identifying a model-predicted anthropogenic fingerprint in satellite measurements of annual-mean tropospheric temperature. The MSU and AMSU measurements are from three different research groups: Remote Sensing Systems (RSS), the Center for Satellite Applications and Research (STAR), and the University of Alabama at Huntsville (UAH). The grey and black horizontal lines are the 3σ and 5σ thresholds that we use for estimating the signal detection time. By 2002, all three satellite datasets yield S/N ratios exceeding the 3σ threshold. By 2016, an anthropogenic signal is consistently detected at the 5σ threshold. Further details of the model and satellite data and the fingerprint method are provided in the online Methods.

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228 **Disclaimer:** The views, opinions, and findings contained in this report are those of the au-

229 thors and should not be construed as a position, policy, or decision of the U.S. Government,
230 the U.S. Department of Energy, or the National Oceanic and Atmospheric Administration.

231 **Online Methods**

232 **1 Satellite atmospheric temperature data**

233 In calculating the signal detection times shown in Figure 1, we used satellite estimates of
234 atmospheric temperature produced by Remote Sensing Systems^{5,26}, the Center for Satellite
235 Applications and Research^{27,28}, and the University of Alabama at Huntsville^{29,30}. We refer
236 to these groups subsequently as RSS, STAR, and UAH (respectively). All three groups
237 provide satellite measurements of the temperatures of the mid- to upper troposphere (TMT)
238 and the lower stratosphere (TLS). Our focus here is on estimating the detection time for an
239 anthropogenic fingerprint in satellite TMT data. TLS is required for correcting TMT for
240 the influence it receives from stratospheric cooling²⁴ (see Section 3).

241 Satellite datasets are in the form of monthly means on $2.5^\circ \times 2.5^\circ$ latitude/longitude
242 grids. At the time this analysis was performed, temperature data were available for the
243 468-month period from January 1979 to December 2017. We used the most recent dataset
244 versions from each group: 4.0 (RSS), 4.0 (STAR), and 6.0 (UAH).

245 We note that studies of the size, patterns, and causes of atmospheric temperature changes
246 have also relied on information from radiosondes^{20,31,32,33,34}. Non-climatic factors, such
247 as refinements over time in radiosonde instrumentation and thermal shielding, hamper the
248 identification of true climate changes^{20,35}. Additionally, radiosonde data have much sparser
249 coverage than satellite data, particularly in the Southern Hemisphere. The spatially com-
250 plete coverage of MSU and AMSU offers advantages for obtaining reliable estimates of

251 hemispheric- and global-scale temperature trends and patterns of temperature change.

252 **2 Details of model output**

253 We used model output from phase 5 of CMIP, the Coupled Model Intercomparison Project³⁶.

254 The simulations analyzed here were contributed by 19 different research groups (see Sup-
255 plementary Table S1). Our focus was on three different types of numerical experiment:

256 1) simulations with estimated historical changes in human and natural external forcings;

257 2) simulations with 21st century changes in greenhouse gases and anthropogenic aerosols
258 prescribed according to the Representative Concentration Pathway 8.5 (RCP8.5), with ra-

259 diative forcing of approximately 8.5 W/m^2 in 2100, eventually stabilizing at roughly 12
260 W/m^2 ; and 3) pre-industrial control runs with no changes in external influences on climate.

261 Details of these simulations are provided in Supplementary Tables S2 and S3.

262 Most CMIP5 historical simulations end in December 2005. RCP8.5 simulations were
263 typically initiated from conditions of the climate system at the end of the historical run.

264 To avoid truncating comparisons between modeled and observed atmospheric temperature
265 trends in December 2005, we spliced together synthetic satellite temperatures from the

266 historical simulations and the RCP8.5 runs. Splicing allows us to compare actual and

267 synthetic temperature changes over the full 39-year length of the satellite record. We use

268 the acronym “HIST+8.5” to identify these spliced simulations.

269 **3 Method used for correcting TMT data**

270 Trends in TMT estimated from microwave sounders receive a substantial contribution from
271 the cooling of the lower stratosphere^{24,37,38,39}. In Fu et al. (2004)²⁴, a regression-based
272 method was developed for removing the bulk of this stratospheric cooling component of
273 TMT. This method has been validated with both observed and model atmospheric temper-
274 ature data^{37,40,41}. Here, we refer to the corrected version of TMT as TMT_{cr} . The main text
275 discusses corrected TMT only, and does not use the subscript cr to identify corrected TMT.

276 For calculating tropical averages of TMT_{cr} , Fu et al. (2005)³⁸ used:

$$TMT_{cr} = a_{24}TMT + (1 - a_{24})TLS \quad (1)$$

277 where $a_{24} = 1.1$. For the global domain considered here, lower stratospheric cooling makes
278 a larger contribution to TMT trends, so a_{24} is larger^{24,39}. In Fu et al (2004)²⁴ and Johanson
279 and Fu (2006)³⁹, $a_{24} \approx 1.15$ was applied directly to near-global averages of TMT and TLS.
280 Since we are performing corrections on local (grid-point) data, we used $a_{24} = 1.1$ between
281 $30^\circ N$ and $30^\circ S$, and $a_{24} = 1.2$ poleward of 30° . This is approximately equivalent to use of
282 the $a_{24} = 1.15$ for globally-averaged data.

283 **4 Calculation of synthetic satellite temperatures**

284 We use a local weighting function method developed at RSS to calculate synthetic satellite
285 temperatures from model output⁴². At each model grid-point, simulated temperature pro-
286 files were convolved with local weighting functions. The weights depend on the grid-point

287 surface pressure, the surface type (land or ocean), and the selected layer-average tempera-
288 ture (TLS or TMT).

289 **5 Fingerprint method**

290 Detection methods generally require an estimate of the true but unknown climate-change
291 signal in response to an individual forcing or set of forcings^{16,17,43,44,45,46}. This is often
292 referred to as the fingerprint $F(x)$.

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

296

297 $i = 1, \dots, N_r(j)$ (the number of realizations for the j^{th} model).

298 $j = 1, \dots, N_m$ (the number of models used in fingerprint estimation).

299 $x = 1, \dots, N_x$ (the total number of grid-points).

300 $t = 1, \dots, N_t$ (the time in years).

301

302 Here, N_r ranges from 1 to 5 realizations and $N_m = 37$ models. After transforming syn-
303 thetic MSU temperature data from each model's native grid to a common $10^\circ \times 10^\circ$ lati-
304 tude/longitude grid, $N_x = 576$ grid-points for corrected TMT. N_t is 39 years. We note that
305 because the RSS TMT data do not have coverage poleward of 82.5° , the latitudinal extent

306 of the regridded data is from 80°N to 80°S. This is the minimum common coverage in the
307 three satellite datasets.

308 The multi-model average atmospheric temperature change, $\overline{\overline{S}}(x, t)$, was calculated by
309 first averaging over an individual model's HIST+8.5 realizations (where multiple realiza-
310 tions were available), and then averaging over models. The double overbar denotes these
311 two averaging steps. Anomalies were then defined at each grid-point x and year t with
312 respect to the local climatological annual mean. The fingerprint $F(x)$ is the first Empirical
313 Orthogonal Function (EOF) of the anomalies of $\overline{\overline{S}}(x, t)$. $F(x)$ was estimated over 1979 to
314 2017, the same time period used for determining observed TMT changes.

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

319 We obtain these variability estimates from control runs performed with multiple mod-
320 els. Because the length of the 36 control runs analyzed here varies by a factor of up to
321 4, models with longer control integrations could have a disproportionately large impact on
322 our noise estimates. To guard against this possibility, the noise estimates rely on the last
323 200 years of each model's pre-industrial control run, yielding 7,200 years of concatenated
324 control run data. Use of the last 200 years reduces the contribution of any initial residual
325 drift to noise estimates.

326 Synthetic TMT data from individual model control runs are regridded to the same $10^\circ \times$
 327 10° target grid used for fingerprint estimation. After regridding, anomalies are defined
 328 relative to the local climatological annual means calculated over the full length of each
 329 control run. Since control run drift can bias S/N estimates, its removal is advisable. Here,
 330 we assume that drift behavior can be well-approximated by a least-squares linear trend, and
 331 drift is removed at each grid-point. Drift removal is performed over the last 200 control run
 332 years (since only the last 200 years are concatenated).

333 Observed annual-mean TMT data are first transformed to the $10^\circ \times 10^\circ$ latitude/longitude
 334 grid used for the model HIST+8.5 simulations and control runs, and are then expressed as
 335 anomalies relative to climatological annual means over 1979 to 2017. The observed tem-
 336 perature data are projected onto $F(x)$, the time-invariant fingerprint:

$$Z_o(t) = \sum_{x=1}^{N_x} O(x, t) F(x) \quad t = 1, 2, \dots, 39 \quad (2)$$

337 where $O(x, t)$ denotes the observed annual-mean TMT data. This projection is equivalent
 338 to a spatially uncentered covariance between the patterns $O(x, t)$ and $F(x)$ at year t . The
 339 signal time series $Z_o(t)$ provides information on the fingerprint strength in the observations.
 340 If observed patterns of temperature change are becoming increasingly similar to $F(x)$,
 341 $Z_o(t)$ should increase over time. A recent publication⁴⁷ provides figures showing both
 342 $F(x)$ and the observed patterns of annual-mean trends in TMT (see Figure S5A and Figures

343 2A,C, and E in Santer *et al.*, 2018).

344 Hasselmann’s 1979 paper discusses the rotation of $F(x)$ in a direction that maximizes
345 the signal strength relative to the control run noise¹⁷. Optimization of $F(x)$ generally
346 leads to enhanced detectability of the signal^{48,49}. In all cases we considered, we achieved
347 detection of an externally-forced fingerprint in satellite TMT data without any optimization
348 of $F(x)$. We therefore show only non-optimized results in our Figure 1.

349 Finally, we note that all model and observational temperature data used in the finger-
350 print analysis are appropriately area-weighted. Weighting involves multiplication by the
351 square root of the cosine of the grid node’s latitude⁵⁰.

352 **6 Estimating detection time**

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

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

359 Our detection time T_d is based on the signal-to-noise ratio, S/N. As in our previous
360 work⁴⁷, we calculate S/N ratios by fitting least-squares linear trends of increasing length
361 L years to $Z_o(t)$, and then comparing these with the standard deviation of the distribution
362 of non-overlapping L -length trends in $N_c(t)$. Thus the numerator of the S/N ratio mea-
363 sures the trend in the pattern agreement between the model-predicted “human influence”
364 fingerprint and observations; the denominator measures the trend in agreement between
365 the fingerprint and patterns of natural climate variability. Detection occurs after L_d years,
366 when the S/N ratio first exceeds some stipulated signal detection threshold, and then re-
367 mains continuously above that threshold for all values of $L > L_d$. For example, $L_d = 10$
368 would signify that $T_d = 1988 - i.e.$, that detection of a human-caused tropospheric warming
369 fingerprint occurred in 1988, 10 years after the start of the satellite temperature record.

370 We estimated T_d with both 3σ and 5σ signal detection thresholds. A 3σ threshold
371 was used by Hansen et al. (1988) for detection of an anthropogenic signal in surface
372 temperature⁵¹. A more stringent 5σ threshold is often employed as the gold standard for
373 scientific discovery in particle physics* For detection at a 3σ threshold, there is a chance
374 of roughly one in 741 that the “match” between the model-predicted anthropogenic finger-
375 print and the observed patterns of tropospheric temperature change could actually be due
376 to natural internal variability (as represented by the 36 models analyzed here). With a 5σ
377 detection threshold, this probability decreases to roughly one in 3.5 million[†].

*For example, in detecting the existence of the Higgs boson. See, e.g., <https://understandinguncertainty.org/explaining-5-sigma-higgs-how-well-did-they-do>.

[†]These are so-called complementary cumulative probabilities – see, e.g., <https://en.wikipedia.org/wiki/>

378 We make three assumptions in order to calculate T_d . First, we assume that our knowl-
379 edge of observed tropospheric temperature change is derived from the latest MSU and
380 AMSU dataset versions produced by RSS, UAH, and STAR. Second, we assume that large
381 ensembles of forced and unforced simulations performed with state-of-the-art climate mod-
382 els provide the best current estimates of a human fingerprint and natural internal climate
383 variability⁴⁷. Third, we assume that although the strength of the fingerprint in the observa-
384 tions changes over time, the fingerprint pattern itself is relatively stable⁴⁷.

385 At the 3σ threshold, $T_d = 1998$ for RSS and STAR and 2002 for UAH (Figure 1).
386 This means that L_d is 20 years for RSS and STAR and 24 years for UAH. With a more
387 stringent 5σ threshold the detection time is longer: $T_d = 2003$ for STAR, 2005 for RSS,
388 and 2016 for UAH, yielding L_d values of 25, 27, and 38 years, respectively. The UAH
389 results are noteworthy. Even though UAH tropospheric temperature data have consistently
390 shown less warming than other datasets^{24,52,53,54}, UAH still yields confident 5σ detection
391 of an anthropogenic fingerprint.

392 Finally, we note that detection times for an anthropogenic signal in surface temperature
393 are available elsewhere^{43,44,45,51} and have been the topic of recent discussion[‡].

Standard_normal_table#Cumulative. 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 satellite data.

[‡]Another scientific anniversary received considerable attention in 2018 – the 30th anniversary of the publication of a seminal paper by Jim Hansen and his colleagues at the NASA/Goddard Institute for Space Studies⁵¹. Some of the recent reporting on the 1988 Hansen et al. paper focused on the paper’s prediction that “the global greenhouse warming should rise above the level of natural climate variability within the next several years”. This prediction was for global-mean changes in surface temperature. It relied on a comparison of observed changes with multiple estimates of natural variability.

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