Erroneous use of Statistics behind Claims of a Major Solar Role in Recent Warming

Mark T. Richardson^{1,2} and Rasmus E. Benestad³ ¹ Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA 91109, USA; markr@jpl.nasa.gov ² Department of Atmospheric Science, Colorado State University, Ft Collins, CO 90732, USA ³ Norwegian Meteorological Institute, NO-0313 Oslo, Norway

Received 2022 February 21; revised 2022 September 2; accepted 2022 September 5; published 2022 November 16

Abstract

In a study that attempted to relate solar and human activity to Earth's recent temperature change, Connolly et al. committed a basic error in the choice of statistical methods and so overreported the effect of the Sun. A major theme of their study was that there are many data sets of past solar activity, and some of these allegedly provide statistical evidence of "most of the recent global warming being due to changes in solar activity." We avoid methods that are known to give inaccurate results and show that for 1970-2005 Northern Hemisphere land the corrected solar attribution fraction is -7% to +5%, compared with values of up to 64% reported in Connolly et al. Their higher values are entirely due to mistaken application of statistics. Unfortunately, we cannot test truly "recent" global warming since most of their solar data sets end before 2015, and two finish in the 1990s, but all tested post-1970 periods show similarly small solar contributions. The solar-climate linkage is an area of fascinating and ongoing research with rigorous technical discussion. We argue that instead of repeating errors, they should be acknowledged and corrected so that the debate can focus on areas of legitimate scientific uncertainty.

Key words: Earth – (Sun:) solar-terrestrial relations – Physical Data and Processes

1. Introduction

Connolly et al. (2021) recently made unsubstantiated claims about the evidence for how total solar irradiance (TSI) has contributed to recent climate change. The specious assertion of some quantitative evidence in support of their position is primarily because they select a statistical method which is well known to give inaccurate results in these conditions, namely sequential rather than simultaneous regression.

In simple terms: if multiple covarying factors are affecting global temperature ΔT at the same time, then the statistical methods should calculate their effects at the same time. In this case, the factors considered are solar forcing ΔF_{TSI} and humancaused (anthropogenic) forcing ΔF_{anthro} . Over 1850–2005 these factors covary, with mean correlation r of 0.55 across TSI data sets, and a maximum of 0.77 for one ΔF_{TSI} data set. Rather than calculating the effects of ΔF_{TSI} and ΔF_{anthro} at the same time, Connolly et al. first regress ΔT against ΔF_{TSI} alone, and due to the correlation between ΔF_{TSI} and ΔF_{anthro} , this will attribute some of the human-caused warming to the Sun. They could just as easily have chosen to perform the calculation first against ΔF_{anthro} , in which case the results are completely different, and some of the solar-caused ΔT change would be attributed to human activity. They chose to report the results of the first erroneous calculation, which overemphasizes the contribution of the Sun, but not the results of the second which would understate the solar fraction.

Either sequential ordering is well-known to give inaccurate results, so the standard approach is to perform a simultaneous regression (Foster & Rahmstorf 2011; Schmidt et al. 2014; Saenko et al. 2016; Hu & Fedorov 2017; Folland et al. 2018; Meng et al. 2021). Here we show using Monte Carlo tests that the Connolly et al. method is, indeed, strongly biased in favor of overreporting the solar contribution to warming. Applying standard multiple regression, which is unbiased in the Monte Carlo tests, we show that the data support anything from slight solar-induced cooling to slight warming in recent decades.

We focus on the sequential regression issue because it is uniquely necessary to support Connolly et al.'s claim of a major solar role in recent warming, which contradicts other evidence. This paper will briefly address other statistical shortcomings to provide more accurate and robust attribution estimates, but this statistical focus should not be taken to mean that Connolly et al. is otherwise free of statements that rely on flawed or selective use of evidence.

There is a fascinating and science-based debate on solarweather and solar-climate relationships. However, we strongly argue that a useful and productive debate requires using data and mathematical techniques that are tested and shown to be reliable. Conclusions that have been shown to be false should be ignored in favor of accuracy, rather than repeated in favor of maintaining the appearance of a broader debate.



This comment includes an analysis of the Connolly et al. data in Section 2, a brief discussion of those and other issues in Section 3, and conclusions and recommendations in Section 4.

2. Statistical Analysis

The Connolly et al. attribution method is to statistically decompose ΔT into contributions from TSI ($\Delta T_{\text{TSI}}(t)$) and human-caused factors ($\Delta T_{\text{anthro}}(t)$), and then to derive their linear trends and compare those trends with that of $\Delta T(t)$. The issues and limitations with their approach include:

- 1. Use of sequential rather than simultaneous regression,
- 2. Linear regression to quantify changes in the nonlinear $\Delta T(t)$ series,
- 3. Drawing conclusions using results calculated from other periods, such as one case where changes in "recent decades" are based on an 1815–1994 fit,
- 4. Lack of assessment of any uncertainties,
- 5. Use of non-global data (e.g., Northern Hemisphere (NH) land) to make assertions about global changes,
- 6. That this is a purely correlational analysis and does not consider physics.

This section will primarily address 1–4 via a combination of Monte Carlo tests and analysis of much of the same data used in Connolly et al.

2.1. Order of Regression

2.1.1. Monte Carlo Tests

A standard way to validate statistical methods is to use Monte Carlo simulations in which a system is constructed following some model assumptions with known true parameters. Proposed statistical methods are then applied to determine whether they accurately obtain the true parameters or other relevant information, such as their confidence intervals. Methods which have large biases should be discarded. In this case it is assumed that temperature can be decomposed as follows

$$\Delta T = \Delta T_0 + a_{\text{TSI}} \Delta T_{\text{TSI}} + a_{\text{anthro}} \Delta F_{\text{anthro}} + \epsilon.$$
(1)

Here ΔT_0 is an intercept that represents an arbitrary temperature offset and will change with the selected ΔT anomaly baseline period. ΔF_{TSI} and ΔF_{anthro} are linearly related to temperature by parameters labeled *a*, and the term ϵ represents noise. For these tests noise is generated following an AR(1) process with lag-1 correlation of 0.3 and a standard deviation of 0.3°C, and for a_{TSI} and a_{anthro} we select several parameter combinations. The $\Delta F_{\text{TSI}}(t)$ in this case is that recommended for the Coupled Model Intercomparison Project, Phase 6 (CMIP6) (Matthes et al. 2017) and ΔF_{anthro} is that for CMIP5 (Meinshausen et al. 2011).

For each combination of properties, we generate 5000 pseudorandom $\epsilon(t)$ series and perform sequential and multiple

regression on each one to provide 15,000 parameter estimates: 5000 for multiple regression, and 5000 for each ordering of sequential regression. Figure 1(a) shows constructed $\Delta T(t)$ series and Figure 1(b)–(d) confirms that, as stated in Section 1, sequential regression is biased. The magnitude and direction of the bias depend on the order in which regression is performed, and on the relative contribution of each variable. In the case where the variance explained by solar activity is small (Figure 1(c)), the Connolly et al. method artificially inflates the solar contribution by approximately 4000%.

This poor performance confirms that the Connolly et al. method should be discarded, while the standard multiple regression approach passes this test.

2.1.2. Connolly et al. Results

Figure 2 displays regression results using the Connolly et al. "urban and rural" $\Delta T(t)$ with $\Delta F_{\text{TSI}}(t)$ from two sources, one featuring "high-variability" from Hoyt & Schatten (1993), Scafetta & Willson (2014) (Figure 2(a)–(c)) and one showing "low-variability" from Steinhilber et al. (2009) (Figure 2(d)– (f)). These were two of the 16 TSI data sets that were claimed to support that most of the recent warming is solar-driven.

Figures 2(a) and (d) reproduce Connolly et al. values and Figures 2(b) and (e) the results they briefly discussed but elected not to show, which is when the ΔF_{anthro} fit is done first and the TSI attribution fraction shrinks to below 10%. The enormous change in conclusion depending on the order of the calculation further makes it obvious that this is an inappropriate method. Multiple regression results are in Figures 2(c) and (f) and affirm that the statistical evidence supports small ΔT_{TSI} changes in recent decades over NH land.

Figure 2 also demonstrates that variability appears larger earlier in the record and that the $\Delta T(t)$ series are nonlinear. The uses of ordinary least squares (which assumes time-constant uncertainties) and linear regression to derive temperature trends are therefore choices which should have been tested for robustness.

2.2. Nonlinearities and Uncertainties

For each combination of data sets, Connolly et al. estimated recent ΔT change from the full-period linear trend. For example, the Hoyt & Schatten $\Delta F_{\text{TSI}}(t)$ spans 1700–2018 and the Urban & Rural NH land temperature data cover 1815–2018. The regression was performed over the longest common period 1815–2018. These long-term linear trend estimates were the basis of their attribution statement referring to temperature change in "recent decades," or in reference to the Intergovernmental Panel on Climate Change (IPCC) attribution statement regarding warming since 1950.

The long-term relationship between ΔT and ΔF is expected to be approximately linear for the magnitude of ΔT considered here, but it has been clearly demonstrated that global ΔT is

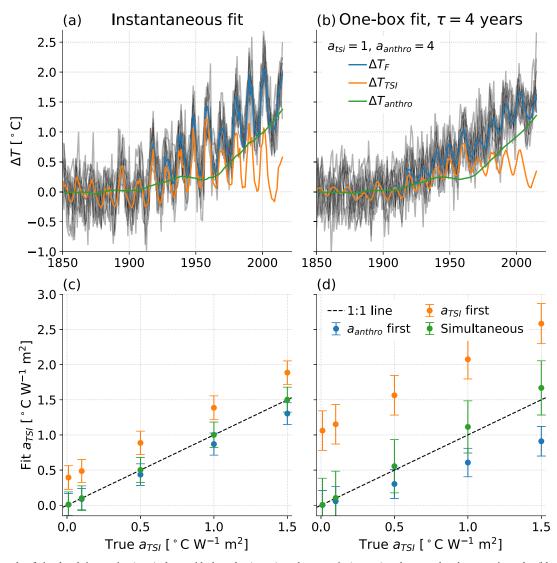


Figure 1. (a) Example of simulated time series (gray) along with the solar (green), anthropogenic (orange) and summed anthropogenic+solar (blue) ΔT . Each gray line is a single replicate consisting of the blue line plus pseudorandomly generated AR(1) noise. This panel uses $a_{TSI} = 1$ and $a_{anthro} = 4$. (b) Regression estimates of a_{TSI} derived from 5000 replicates using Connolly et al. sequential regression (blue), with a flipped sequence, i.e., regress against ΔF_{anthro} first (orange) and using multiple regression (green). (c) The same but with a dominant anthropogenic contribution to ΔT , and (d) with a dominant solar contribution.

nonlinear in time since the 1800s (Cahill et al. 2015). The same is true of NH land ΔT over 1815–2018, so century-plus linear trends are poor estimators of recent change. Furthermore, two of the TSI data sets reported by Connolly et al. to support >50% ΔT_{TSI} contribution ended in 1994 and 1998. It is a bizarre choice to exclude the last 20+ yr from the definition of "recent decades," so we ignore those TSI series from now on.

Connolly et al. do not define "recent decades" but we will illustrate by comparing 1970–2018 ΔT from a linear trend, an 1815–2018 linear trend and a 40 yr windowed LOESS (Cleveland 1979) which has been shown to reliably capture forced temperature changes (Clarke & Richardson 2021). Figure 3 demonstrates that recent warming is approximately 200% larger than estimated from the unsuitable 1815–2018 linear fit. This Connolly et al. choice inflates the 3% 1970–2018 ΔT_{TSI} contribution to 9%.

A further consideration is that the physical ΔT change during 1970–2018 should not depend on changes during, for example, 1815–1880. However, shifting the regression start date to 1880 changes the Connolly estimate of 1970–2018 warming by approximately 50%, while the LOESS result changes by <1%. This linearity refers specifically to trends in time, i.e., $d\Delta t/dt$. As summarized in Equation (1), the Connolly et al. attribution assumes relationships between ΔF terms and ΔT to be linear and constant. If true, then it is desirable to use the longest possible period to derive a_{TSI} and

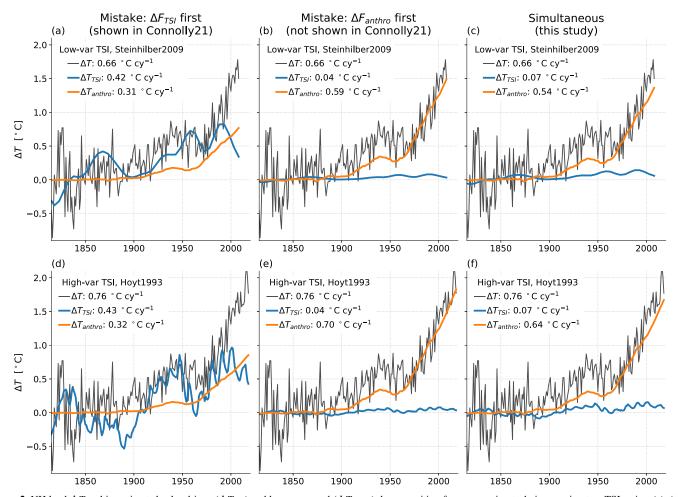


Figure 2. NH land ΔT and its estimated solar-driven (ΔT_{TSI}) and human-caused (ΔT_{anthro}) decomposition from regression techniques using two TSI series; (a)–(c) a "high variability" version from Hoyt & Schatten (1993), Scafetta & Willson (2014) and (d)–(f) a "low variability" version from Steinhilber et al. (2009). The column headed (a) uses Connolly et al.'s TSI-first regression. The column headed (b) is the same, but with anthropogenic regression first. The column headed (f) is multiple regression that does not favor one predictor over the other. The legends report the full-period linear trends for each component, which match the values used in Connolly et al.'s "attribution" in Figures 15 and 16. Note ΔT trends differ because (a)–(c) spans 1815–2008 while (d)–(f) spans 1815–2018.

 a_{anthro} , since more data generally reduce fit uncertainty. However, when uncertainty changes in time, standard optimized least squares (OLS) overfits to the less-certain data. In this case pre-1900 $\Delta T(t)$ data will be overfit relative to the post-1900 data.

Figure 4 depicts NH land $\Delta T(t)$ uncertainty and demonstrates how OLS-estimated a_{TSI} changes by ±50% as regression start dates are moved between 1815 and 1850. This is important for consistent comparisons, since the start date of the solar reconstructions varies. Using weighted least squares to account for $\Delta T(t)$ uncertainty provides more stable estimates of both a_{TSI} and a_{anthro} . Another notable absence from Connolly et al. was estimates of regression errors. While a_{anthro} is significant and positive in all cases, for several TSI data sets a_{TSI} is not significant (p < 0.05), i.e., the influence of TSI on long-term ΔT is statistically indistinguishable from 0.

Now that stable estimates are possible for a variety of start dates, it is possible to estimate the solar contribution to recent warming following the principle of Connolly et al.'s statistical method, but by avoiding approaches that give provably inaccurate results.

2.3. Corrected Statistical Estimates of Warming in recent Decades due to TSI Changes

Here we recalculate the attribution fraction for 1970–2005 warming with the methodological updates described in Sections 2.1–2.2, namely:

- 1. Simultaneous multiple regression to estimate a_{TSI} and a_{anthro} , over the largest common overlap period, typically starting in 1815 or 1850,
- 2. LOESS for 1970–2005 ΔT change,

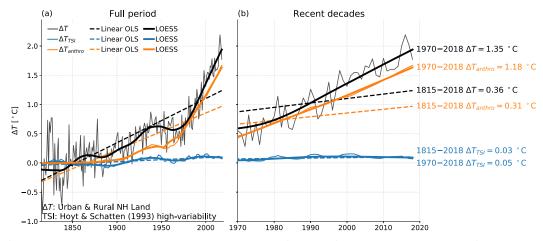


Figure 3. NH land ΔT and its simultaneous multiple regression decomposition into ΔF_{TSI} and ΔF_{anthro} using Hoyt & Schatten ΔF_{TSI} and Meinshausen historical-RCP6.0 ΔF_{anthro} . (a) Full period, (b) since 1970. The 1815–2018 linear OLS fits used for attribution in Connolly et al. are drawn as dashed lines, and LOESS fits following Clarke & Richardson as thick solid lines. Text on the right reports the 1970–2018 ΔT estimated following Connolly et al. vs. Clarke & Richardson.

3. Weighted-least squares regression using the $\Delta T(t)$ uncertainties.

There are minor changes in numbers but the conclusions are the same for 1950–2005, 1970–2014 or 1950–2014; 14 of the 16 TSI series extend through 2005 and 9 through 2014. For $\Delta T(t)$ we use validated data sets that span these time periods, namely the urban and rural NH land series from Connolly et al. with the extended Berkeley Earth uncertainty estimates as in Section 2.2, HadSST4 NH sea-surface temperatures (Kennedy et al. 2019), and HadCRUT5 global land-ocean surface temperatures (Morice et al. 2020).

Figure 5 shows that the conclusions from Sections 2.1 and 2.2 hold across all TSI data sets. The flawed method used by Connolly et al. generates a wide range of solar attribution estimates, from 0% to 70%, and supports discussion about the possibility of a predominant role for solar activity in recent warming. The orange lines show that part of this is due to their preference for including data from the 1800s to quantify warming in recent decades.

Even with the biased simultaneous regression, simply using data from recent decades to calculate recent-decade ΔT reduces the mean solar contribution from 40% to 24% for NH land, and 39% to 14% for global data, compared with the Connolly et al. approach of including data from the 1800s to calculate recent-decade ΔT changes.

However, the primary reason that Connolly et al. generated wide ranges in solar attribution fraction was the inappropriate use of sequential regression. The multiple regression results provide a more tightly constrained estimate of the solar contribution to warming which, for NH land, is centered around 1% of total warming. The highest fraction it is possible to obtain is 14% of SST warming from the Egorova et al. (2018) "PHI-MU16" TSI series. The statistically estimated

anthropogenic contribution to global warming over 1970–2005 is 84%–101%, although independent evidence suggests that higher values are plausible.

3. Discussion

3.1. Interpretation of Attempted Statistical Attribution Results

In 2013 the IPCC stated that "human influence has been the dominant cause of the observed warming since the mid-20th century," and this conclusion was disputed as being made "prematurely" by Connolly et al., who claimed that "the use of many of the "high solar variability" TSI estimates could imply a much greater role for the Sun."

This conclusion was surprising given that, as can be seen in Figure 6, the largest differences between TSI data sets occur before 1950. Larger ΔF_{TSI} variability implies smaller $a_{\text{TSI}} = d\Delta T/d\Delta F_{\text{TSI}}$ and therefore smaller recent ΔT_{TSI} . However, Connolly et al. assert the opposite: 7/8 of the "high-variability" solar series resulted in >50% of recent solar warming attribution, compared with 1/8 of the "low-variability" series. Here we have shown this counter-logical conclusion is the result of selecting statistical approaches that demonstrably fail for this application.

The authors noted that members of their team had in 2015 identified that sequential regression produces unstable results (Soon et al. 2015) and it seems remarkable that it was not realized that this instability invalidates their chosen methodology. The reason given for not using more reliable approaches seems to be: "it might be argued that the various contributions should be estimated simultaneously. We caution that there is a distinction between the TSI estimates that are calibrated against empirical measurements (i.e., satellite measurements) and anthropogenic forcings that are usually

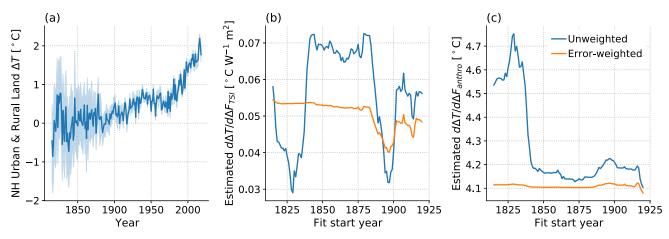


Figure 4. (a) NH land urban and rural temperature series as used in Connolly et al. with $\pm 2\sigma$ uncertainties from Berkeley Earth NH land added as shading. Pre-1840 uncertainties repeat the 1840 uncertainties. (b) Regression sensitivity of temperature to TSI forcing as a function of start year of the regression for Connolly et al. unweighted and error-weighted regression, and (c) same but for anthropogenic forcing sensitivity.

calculated from theoretical modeling." These comments are linked grammatically, but not logically.

3.2. Limitations of Approach

Climate change attribution is hugely complex and IPCC attribution statements rely on multiple lines of evidence. The only quantitative evidence presented by Connolly et al. to dispute this was based on the use of inappropriate statistical methods that are known to give inaccurate results. When avoiding these errors, there is no quantitative evidence in support of a large solar activity contribution to recent global surface warming. Of course, these statistical techniques still make assumptions, but it is not clear whether or how far violations of these assumptions translate into errors in attribution results. Equation (1) assumptions include:

- 1. ΔF_{TSI} and ΔF_{anthro} effects on temperature are independent of each other,
- 2. all major forcing agents are captured,
- 3. there is an instantaneous, fixed and linear relationship captured by a_{TSI} and a_{anthro} .

In the wider literature, physical considerations are used to assess these assumptions. We are unaware of evidence for an interaction between solar and anthropogenic effects that is large relative to ΔF_{anthro} , so assumption (1) should hold to a reasonable approximation. Assumption (2) is not exactly true, since volcanism can exert large ΔF_{volc} . Connolly et al. note that it is episodic and conclude that it will have little effect on recent-decade attribution; we confirmed this by repeating the calculations and including ΔF_{volc} from Meinshausen et al. (2011). In this case, the solar attribution fraction narrows slightly, with a range from -2% to +4% of NH land warming over 1970–2005. The results therefore appear robust to credible violations of assumption (2). While assumptions (1) and (2) appear unlikely to greatly affect the results, assumption (3) is more complex. First, the relationship between changes in ΔF and ΔT is not instantaneous because of the Earth's thermal inertia, as discussed in Connolly et al. However, the similarity of the results when using a one-box energy balance model suggests that the general conclusions would not change solely due to Earth's inertia.

However, there has been extensive recent research demonstrating that the efficiency of heat uptake and radiative feedbacks to temperature change can vary in time. This can be due to nonlinearities and hysteresis (Schneider et al. 2019), or due to differing responses to spatially varying warming (Zhou et al. 2016; Andrews et al. 2018). Notably, this modern research provides specific physical processes to explain the relationships, many of which have been directly measured. Independent approaches applied to separate satellite instruments agree on overall changes in Earth's energy budget associated with this effect (Kramer et al. 2021). Including physical understanding is crucial context for the discussion of recent climate change, and is another major reason why the discussion in Connolly et al. differs from that of the IPCC. However, a full description would greatly extend this paper and so readers are directed to the IPCC assessments (Stocker 2013; Masson-Demotte et al. 2021).

3.3. Failure to Account for Relevant Information

Another weakness in the work presented by Connolly et al. is neglect of important relevant information, or repetition of results that were later shown to be unfounded without informing the reader that those results were spurious.

For example, there was no mention of the most recent comprehensive and state of the art analysis of the solar-climate link conducted through the European project COST-Tosca that was assessed in Lilensten et al. (2015), which also explains that

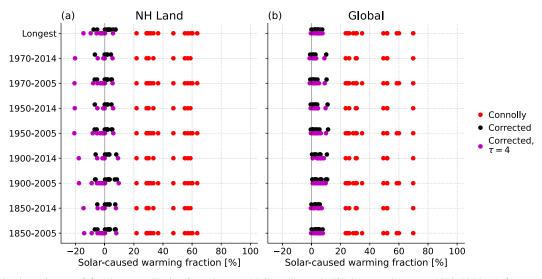


Figure 5. Kernel-density estimates of ΔT change attribution from the N = 14 Connolly et al. TSI data sets that cover 1970–2005. (a) ΔF_{TSI} and NH land ΔT , (b) ΔF_{TSI} and HadSST4 NH ocean ΔT , (c) ΔF_{TSI} and HadCRUT5 global ΔT , and (d) ΔF_{anthro} and global ΔT . Blue lines are from the Connolly et al. method, orange lines the same but with LOESS ΔT change. The green and red lines use multiple regression plus LOESS ΔT change, with green being OLS and red being least squares weighted for $\Delta T(t)$ error. Legends report the mean and range of attribution fraction across TSI data sets.

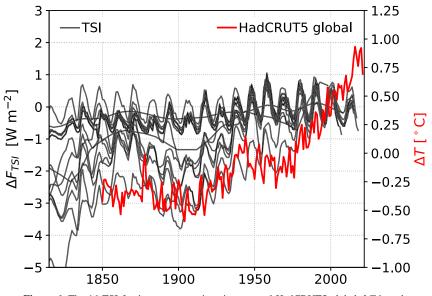


Figure 6. The 16 TSI forcing reconstructions in gray and HadCRUT5 global ΔT in red.

some of the past debate about the solar-terrestrial link was based on inappropriate analysis (Benestad 2015). Furthermore, while Connolly et al. discussed how variations in TSI are accompanied by similar variations in other solar proxies such as the sunspot number, galactic cosmic rays (GCR) and the 10.7 cm radio flux (Benestad 2006), it however did not discuss the missing correlation between GCR and essential climate variables that would be expected if solar activity was a major factor in recent warming (e.g., Benestad 2013).

Connolly et al. is also selective in its reporting of past findings, for example in citing both Scafetta & West (2006a,

2006b) and Benestad & Schmidt (2009), but failing to address that the latter demonstrated how the former misconstrued their analysis. While Friis-Christensen & Lassen (1991) was cited and rightly noted as "disputed," a crucial unmentioned detail is that Friis-Christensen & Lassen's primary conclusion regarding recent warming was entirely the result of a "pattern of strange errors," and once those errors were corrected the evidence no longer supported substantial recent solar-induced warming (Damon & Laut 2004). Another cited study, Humlum et al. (2013), claimed that much atmospheric CO_2 change was not due to human emissions, but Humlum et al. neglected to report

the results relevant to that question. The derived parameters from their data were actually consistent with a $100\% \pm 1\%$ human contribution to atmospheric CO₂ change (Richardson 2013), i.e., the opposite of their stated conclusion. Neither this error nor other issues with that paper (Kern & Leuenberger 2013; Masters & Benestad 2013) were mentioned in Connolly et al.

4. Conclusions

Connolly et al. concluded with a series of recommendations, and we end by arguing strongly in favor of an alternative. Namely, that when conclusions are based solely upon evidence that is found to be wrong, the errors should be acknowledged and corrected. They should not be reiterated solely to further the appearance of a broader debate than that which is supported by the available evidence. Effective debate does not progress by repeating the same mistakes, repeating flawed analyses or repeating inaccurate results, but rather by updating our understanding based on past evidence and exploring new data. In this case, Connolly et al.'s evidence in support of the possibility of a large solar contribution to warming in "recent decades" was purely statistical, and based on faulty application of statistical approaches at that. In order to obtain their results, they made a series of methodological choices that are known to be flawed, but which coincidentally increased the reported solar contribution to warming. This included using data sets that end 2+ decades ago to assess "recent decades," applying linear fits to nonlinear data such that estimated warming in "recent decades" is strongly affected by temperatures in the 1800s and neglecting any assessment of uncertainties.

Most important was the choice of a sequential regression whose results are provably wrong in this situation. There are two ways of doing this calculation incorrectly; the authors noted the existence of both but elected to report only the results from the one that gives a large solar contribution to recent warming. Overall, when modifying the method to remove parts known to give spurious results, the solar contribution to global ΔT over 1970–2014 is less than 3% when using eight of the nine available TSI data sets for that period. The outlier result comes from using the Egorova "PHI-MU" solar record, a "high-variability" record whose statistical attribution is 10% of the 1970–2014 warming. Clearly, a maximum possible value of 10% does not back the claim that there is evidence supporting "most of the recent global warming being due to changes in solar activity."

Given the flaws in the Connolly et al. method, our argument is that their solar conclusions should not be treated as credible and the IPCC statements on solar attribution remain intact. Rather their study should be added to the examples presented by Benestad et al. (2016), helping future researchers to learn from mistakes in climate research.

Acknowledgments

M.R.'s research contribution was carried out at the Jet Propulsion Laboratory, California Institute of Technology, under a contract with the National Aeronautics and Space Administration (80NM0018D0004). R.B.'s contribution was carried out at the Norwegian Meteorological Institute.

ORCID iDs

Mark T. Richardson ^(b) https://orcidorg/0000-0001-7063-631X

References

- Andrews, T., Gregory, G. M., Paynter, D., et al. 2018, GeoRL, 45, 16
- Benestad, R. E. 2006, Solar Activity and Earth's Climate (Chichester: Springer/Praxis)
- Benestad, R. E. 2013, ERL, 8, 035049
- Benestad, R. E. 2015, The debate about solar activity and climate change, Eath's Climate Response to a Changing Sun (Les Elis: EDP Sci.)
- Benestad, R. E., Nuccitelli, D., Lewandowsky, S., et al. 2016, ThApC, 126, 699
- Benestad, R. E., & Schmidt, G. A. 2009, GeoRL, 114, D14101
- Cahill, N., Rahmstorf, S., & Parnell, A. C. 2015, ERL, 10, 084002
- Clarke, D. C., & Richardson, M. T. 2021, E&SS, 8, e2020EA001082
- Cleveland, W. S. 1979, J. Am. Stat. Assoc., 74, 829
- Connolly, R., Soon, W., Connolly, M., et al. 2021, RAA, 21, 131
- Damon, P. E., & Laut, P. 2004, EOS, 85, 370
- Egorova, T., Schmutz, W., Rozanov, E., et al. 2018, A&A, 615, A85
- Folland, C. K., Boucher, O., Colman, A., & Parker, D. E. 2018, SciA, 4, eaao5297
- Foster, G., & Rahmstorf, S. 2011, ERL, 6, 044022
- Friis-Christensen, E., & Lassen, K. 1991, Sci, 254, 698
- Hoyt, D. V., & Schatten, K. H. 1993, JGRA, 98, 18895
- Hu, S., & Fedorov, A. V. 2017, GeoRL, 44, 3816
- Humlum, O., Stordahl, K., & Solheim, J.-E. 2013, GPC, 100, 51
- Kennedy, J. J., Rayner, N. A., Atkinson, C. O., & Killick, R. E. 2019, JGRD, 124, 7719
- Kern, Z., & Leuenberger, M. 2013, GPC, 109, 1
- Kramer, R. J., He, H., Soden, B. J., et al. 2021, GeoRL, 48, e2020GL091585
- Lilensten, J., Dudock de Wit, T., & Matthes, K. 2015, Earth's Climate Response to a Changing Sun (Les Elis: EDP Sci.)
- Masson-Delmotte, V, Zhai, P, Pirani, A, et al. 2021, Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (Cambridge: Cambridge Univ. Press)
- Masters, T., & Benestad, R. 2013, GPC, 106, 141
- Matthes, K., Funke, B., Andersson, M. E., et al. 2017, GMD, 10, 6
- Meinshausen, M., Smith, S. J., Calvin, K., et al. 2011, ClCh, 109, 213
- Meng, L., Liu, J., & Tarasick, D. W. 2021, SciA, 7, eabi8065
- Morice, C. P., Kennedy, J. J., Rayner, N. A., et al. 2020, JGRD, 126, 3
- Richardson, M. T. 2013, GPC, 107, 226
- Saenko, O. A., Fyfe, J. C., Swart, N. C., et al. 2016, CIDy, 47, 2193
- Scafetta, N., & West, B. J. 2006a, GeoRL, 33, L05708
- Scafetta, N., & West, B. J. 2006b, GeoRL, 33, L17718
- Scafetta, N., & Willson, R. C. 2014, Ap&SS, 350, 421
- Schmidt, G. A., Shindell, D. T., & Tsigaridis, K. 2014, NatGe, 7, 158
- Schneider, T., Kaul, C. M., & Pressel, K. G. 2019, NatGe, 12, 163
- Soon, W., Connolly, R., & Connolly, M. 2015, ESRv, 150, 409
- Steinhilber, F., Beer, J., & Frohlich, C. 2009, GeoRL, 36, L19704
- Stocker, T., Dahe, Q., Plattner, G.-K., et al. 2013, IPCC, 2013: Technical Summary. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (Cambridge: Cambridge Univ. Press)
- Zhou, C., Zelinka, M. D., & Klein, S. A. 2016, NatGe, 9, 871