Title: Human-induced global warming estimated using the temperature - accumulated emissions linearity

Authors: Andrew Jarvis[1]*, Piers M. Forster[2]

[1]Lancaster Environment Centre, Lancaster University; Lancaster, LA3 3JB, UK.

[2]Priestley Centre, University of Leeds, LS2 9JT, UK

*Corresponding author. Email: a.jarvis@lancs.ac.uk

Abstract: Global temperature anomaly data underpin all estimates of the magnitude of human-induced warming. However, these data require choosing a pre-industrial baseline in order to create the estimates of the Global Mean Surface Temperature (GMST) change since pre-industrial at the center of all climate science and policy. Currently, this baselining requires choosing a specific 'pre-industrial' period, and adds considerable uncertainty to GMST estimates due to the reliance on the early data record. Here we propose a new more robust method for this rescaling that exploits the observed linearity between the global temperature anomaly and the accumulation of CO_2 emissions in the atmosphere. Using linear regression on this relationship, we estimate the HadCRUT5A anomaly data requires 0.522±0.037 °C adding in order to measure a GMST change since pre-industrial. This linear framework can also be extended to estimate the expected level of warming in near real time, giving a human induced warming in 2022 of 1.441±0.076 °C. This is ~0.2 °C more than is currently estimated and has considerably narrower uncertainties. Our estimate gives a greater than 5 percent chance that the 1.5 °C policy threshold has already been exceeded.

One-Sentence Summary: In order to measure the amount the earth has warmed we must know what the pre-industrial baseline was, and this paper provides a radically better method for doing that.

Main Text:

Introduction

Surface temperature anomaly data are typically centred on their 1960-1990 average value and, as a result, require pre-industrial baselining if they are to represent an absolute measurement of Global Mean Surface Temperature (GMST) change that defines the total human-induced warming estimate. There are different definitions of this preindustrial baseline in the literature, but these are all focused on choosing specific pre-industrial time periods in either temperature anomaly or radiative forcing data ([1], see cross chapter Box 1.2). Given the instrumental temperature record, researchers and the Intergovernmental Panel on Climate Change (IPCC) have made a pragmatic choice to use the 1850-1900 global temperature anomaly as the preferred pre-industrial baseline condition for GMST estimates, given these are the earliest directly observed global temperature data, and the effects of anthropogenic warming are believed to be small 1850-1900 [1,2].

Although the adoption of the 1850-1900 baseline is understandable, it is known that the atmospheric burden of CO_2 is rising both before and throughout this period (Figure 1a), as are anthropogenic carbon emissions driving this increase [3,4]. Several studies have examined the anthropogenic contribution to warming prior to 1850 (see [1], Cross Chapter Box 1.2). Radiative forcing estimates typically assume a 1750 baseline, and based on modelling approaches, these forcings are assessed as adding 0.1 (–0.1 to +0.3) °C to GMST over 1750 to 1850-1900, largely associated with anthropogenic emissions of ~15 GtC [1]. Anthropogenic emissions certainly started significantly earlier than 1750 [5,6] although their importance for temperature has yet to be determined. These findings strongly suggests that GMST is likely to be neither zero or stationary 1850-1900. Furthermore, the 1850-1900 temperature anomaly data are the most uncertain in the global record. As a result, an alternative, more robust pre-industrial baseline method is needed, especially now GMST observations have become central to assessing human induced warming outcomes under the Paris Agreement.

Here, we adopt a different approach to estimating GMST change since pre-industrial for temperature anomaly data that is not based on baselining off of the uncertain early temperature record, but instead baselines against more certain CO_2 ice core data while exploiting the observed linearity between temperature change and cumulative CO_2 emissions [7,8], (see [9] - Figure 5.3.1). This emergent linearity in the behaviour of the Earth system has become central to specifying remaining carbon budgets to meet the 1.5 and 2.0 °C targets set out in Article 2 of the Paris Agreement [9,10]. However, the utility of this relationship extends beyond simply specifying remaining carbon budgets given it can also provide a constraint on the definition of the pre-industrial initial condition. This is because, assuming that pre-industrial non-CO_2 effects are negligible, when no anthropogenic CO_2 has been emitted, any human induced GMST change is, by definition, zero. As a result, in addition to specifying remaining carbon budgets, the GMST-accumulated emissions relationship can also be exploited to estimate levels of human-induced global warming.

We further extend this approach to estimate the expected value of human induced warming i.e. the magnitude of GMST change independent of annual variability. This is the metric against which compliance with the Paris Agreement temperature targets is assessed, and is currently estimated by the IPCC using climate-model attribution studies and statistical trend estimates [11].

Methods

When humans have not added enough CO_2 to the atmosphere to measurably increase the atmospheric burden then, assuming net pre-industrial non-CO_2 effects are also zero at this time, any human induced warming should, by definition, be zero. The atmospheric CO_2 burden is well observed in ice core atmospheric CO_2 data, and this allows us to look back significantly beyond 1850, even significantly before the beginning of the industrial era, to establish a robust pre-industrial baseline for atmospheric CO_2 not reliant on somewhat uncertain emissions inventory data. We take ice core data covering 1006 – 1700 as our baseline condition and use this to specify the post-1700 atmospheric carbon accumulation (ACA; Figure 1a). Post 1850, missing years in the ice core series were interpolated linearly.

We then relate the post-1850 ACA to published global temperature anomaly data. Because the airborne fraction appears to be somewhat conserved historically [9], we predict this temperature anomaly-ACA relationship should be linear given it mirrors the linear Transient Climate Response to cumulative Emissions (TCRE; [8]) relationship extensively used to specify net-zero compliant carbon budgets [9,10]. Any observed linearity allows us to apply regression methods to estimate the equivalent pre-1700 baseline condition for the global temperature anomaly data. We add this regression-estimated baseline to the global temperature anomaly data to produce estimates of GMST change.

We further use the derived linear relationship between GMST change and ACA to estimate the expected value of human-induced warming in any given year based on the corresponding estimates of ACA and the estimated linear scaling between GMST and ACA. Given the timeliness of the release of both the temperature anomaly and atmospheric CO_2 concentration data, allied to the low variance of the latter, this method provides a robust yet simple near-real time method for estimating GMST change suitable to monitoring compliance with the international global temperature targets.

Results

Figure 1a shows the atmospheric CO_2 concentrations reconstructed from the Law Dome ice cores [12] and the Mauna Loa direct air measurements [13]. From this, we estimate a ~700 year (1006 to 1700 AD) pre-industrial baseline for atmospheric CO_2 to be 280.50±5.72 ppmv, or 595.49±12.15 GtC. All subsequent persistent increases above this level can be assumed to be caused by anthropogenic CO_2 emissions, hence defining ACA. However, this is not a requirement; providing we observe linearity in the paired temperature anomaly verses ACA data our method holds.

Figure 1b shows the relationship between the observed ACA (x) and the HadCRUT5A global temperature anomaly data of Morice et al., ([14]; y). This appears strongly linear, both highlighting that any non-CO_2 effects appear largely subsumed within this linearity and lending itself to regression methods. Given the stochastic component of the HadCRUT5A data is approaching an order of magnitude larger than that of the atmospheric CO_2 data (Figure 1a), risk of error-in-variables effects appears small. However, the HadCRUT5A data increase in certainty over time [14], suggesting the need for weighted least squares regression. Using the quoted 95th percentile range for the HadCRUT5A data as the measure of its 2σ uncertainty, we weight the HadCRUT5A data by $1/\sigma$ in the regression $y = mx + c$, which gives $m = 4.916 \pm 0.210$ °C/TtC and $c = -0.522 \pm 0.037$ °C.

From these results it appears the HadCRUT5A data require rescaling by +0.522 °C from their 1961-1990 average to estimate GMST change since our pre-1700 CO_2 concentration baseline period. In comparison, the mean value of the HadCRUT5A data 1850-1900 is -0.359±0.208 °C, suggesting ~0.16 °C of warming is already embedded in the HadCRUT5A data by 1850-1900 in line with estimates from radiative forcing modelling studies (Chen et al., 2021). We stress that, because of the linearity in these paired data, the regression-based estimate for the HadCRUT5A correction utilises the entire 1850-2022 paired data series, not simply the most uncertain data near the origin. Indeed, perfectly reasonable estimates of the HadCRUT5A offset can be obtained from the more certain post-1950 paired data.

To further evaluate our approach, we compare the regression result in Figure 1b with published values of the TCRE, for which the IPCC AR6 provides a pooled estimate of 1.65 (1.0 – 2.3) °C/TtC ([9], Table 5.7). If, on average, non-CO_2 forcings comprise 20 percent of the total [15] and the airborne fraction is 0.44 [9], Figure 1b suggests a TCRE of 1.731±0.074 °C/TtC i.e. close to the current median expected value.

In 2022, the anthropogenic contribution to the atmospheric CO_2 burden was 0.293 TtC and, therefore, our expected value of human induced warming in 2022 is (0.293)(4.880) = 1.441±0.076 °C. The IPCC sixth assessment report employed three statistical methods based on climate models, radiative forcing and temperature data to estimate human-induced warming [11]. These three approaches have been updated to provide an estimate for 2022 of 1.26 °C (1.0 to 1.6 °C) [16]. Compared to these estimates, our straightforward statistical analysis gives 0.18 °C more warming in 2022, which is approximately the additional warming already embedded in the 1850-1900 temperature anomaly baseline.

Policy Implications

If the post 1700 human induced warming is employed, rather than that baselined against the 1850-1900 temperature anomaly data, the world is ~0.2 °C closer to breeching the 1.5 and 2.0 °C targets than currently thought, and the remaining carbon budgets must be proportionately smaller. Furthermore, the 95% prediction interval for the expected value of human induced warming in 2022 includes 1.5 °C using our regression method (Figure 1b), and under expected human induced warming rates around 0.025 °C per year [17] this will more likely than not be passed in under 3 years.

The pre-industrial baseline method for the temperature targets specified under Article 2 of the Paris Agreement has never been defined. One could assume that negotiators had the 1850-1900 baseline in mind given their reliance on IPCC assessed evidence. Therefore, it is not a given that our upwards revision of human-induced warming makes us closer to the Paris limits. It could be argued that the Paris limits also need raising to preserve the level of climate risk the negotiators had in mind with 1.5 °C and 2 °C above an 1850-1900 baseline. However, given the regression method we are proposing appears to offer a superior baseline correction for global temperature anomaly data, certainly some revision of our understanding of the current level of global warming in relation to climate impacts and associated temperature targets is now needed.

It is also important to acknowledge our method for estimating GMST change results in a far narrower uncertainty range for contemporary warming estimates when compared to current IPCC practice. This should significantly aid decision making around this metric, as will the ability to generate this metric near real time given the timeliness of both temperature anomaly and atmospheric CO_2 concentration data availability. It is also likely an advantage that these temperature change estimates are being made within the same framework the climate science community is using to estimate remaining carbon budgets, even though for both the effects of non-CO_2 forcing and changes in the airbourne fraction must not be overlooked. Likewise we must remain mindful of any significant reorganisation of the global energy balance that might also lead to the observed linearity between atmospheric CO_2 concentrations and global temperature change breaking down. However, the framework articulated here could prove useful for detecting any such change given this regression could always be deployed in its recursive form as a means of detecting any such changes.

References and Notes

1. Chen, D., M. Rojas, B.H. Samset, K. Cobb, A. Diongue Niang, P. Edwards, S. Emori, S.H. Faria, E. Hawkins, P. Hope, P. Huybrechts, M. Meinshausen, S.K. Mustafa, G.-K. Plattner, and A.-M. Tréguier, 2021: Framing, Context, and Methods. In Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 147–286, doi:10.1017/9781009157896.003.
2. Gulev, S.K., P.W. Thorne, J. Ahn, F.J. Dentener, C.M. Domingues, S. Gerland, D. Gong, D.S. Kaufman, H.C. Nnamchi, J. Quaas, J.A. Rivera, S. Sathyendranath, S.L. Smith, B. Trewin, K. von Schuckmann, and R.S. Vose, 2021: Changing State of the Climate System. In Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 287–422, doi:10.1017/9781009157896.004.
3. Gilfillan D, Marland G, CDIAC-FF: global and national CO2 emissions from fossil fuel combustion and cement manufacture: 1751–2017, Earth Syst. Sci. Data, 13, 1667–1680, 2021
4. Gasser T, Crepin L, Quilcaille Y, Houghton R, Ciais P, Obersteiner M, Historical CO2 emissions from land use and land cover change and their uncertainty Biogeosciences, 17, 4075–4101, 2020.
5. Ruddiman, W.F. and J.S. Thomson, 2001: The case for human causes of increased atmospheric CH4 over the last 5000 years. Quaternary Science Reviews, 20(18), 1769–1777, doi: 10.1016/s0277-3791(01)00067-1
6. Koch, A., C. Brierley, M.M. Maslin, and S.L. Lewis, 2019: Earth system impacts of the European arrival and Great Dying in the Americas after 1492. Quaternary Science Reviews, 207, 13–36, doi: 10.1016/j.quascirev.2018.12.004.

7. Allen, M., Frame, D., Huntingford, C. et al. Warming caused by cumulative carbon emissions towards the trillionth tonne. Nature 458, 1163–1166 (2009). https://doi.org/10.1038/nature08019

8. Matthews H, Gillett N, Stott P, Zickfeld K, The proportionality of global warming to cumulative carbon emissions, Nature 459, 829–832, 2009.

9. Canadell, J.G., P.M.S. Monteiro, M.H. Costa, L. Cotrim da Cunha, P.M. Cox, A.V. Eliseev, S. Henson, M. Ishii, S. Jaccard, C. Koven, A. Lohila, P.K. Patra, S. Piao, J. Rogelj, S. Syampungani, S. Zaehle, and K. Zickfeld, 2021: Global Carbon and other Biogeochemical Cycles and Feedbacks. In Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 673–816, doi:10.1017/9781009157896.007.

10. Rogelj J, Forster P, Kriegler E, et al., Estimating and tracking the remaining carbon budget for stringent climate targets, Nature 571, 335–342, 2019.

11. Eyring, V., N.P. Gillett, K.M. Achuta Rao, R. Barimalala, M. Barreiro Parrillo, N. Bellouin, C. Cassou, P.J. Durack, Y. Kosaka, S. McGregor, S. Min, O. Morgenstern, and Y. Sun, 2021: Human Influence on the Climate System. In Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 423–552, doi: 10.1017/9781009157896.005

12. Etheridge D, Steele L, Langenfelds R, Francey R, Barnola R-M, Morgan V, Historical CO2 records from the Law Dome DE08, DE08-2, and DSS ice cores. In Trends: A Compendium of Data on Global Change. Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy, Oak Ridge, Tenn., U.S.A. 1998.

13. Keeling R, Piper S, Bollenbacher A, Walker J, Atmospheric CO2 records from sites in the SIO air sampling network. In Trends: A Compendium of Data on Global Change. Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy, Oak Ridge, Tenn., U.S.A. doi: 10.3334/CDIAC/atg.035, 2009.

14. Morice C, Kennedy J, Rayner N, Winn J, Hogan E, Killick R, Dunn R, Osborn T, Jones P, Simpson I, An updated assessment of near-surface temperature change from 1850: the HadCRUT5 dataset. Journal of Geophysical Research (Atmospheres) doi:10.1029/2019JD032361 (supporting information), 2021.

15. Forster, P., T. Storelvmo, K. Armour, W. Collins, J.-L. Dufresne, D. Frame, D.J. Lunt, T. Mauritsen, M.D. Palmer, M. Watanabe, M. Wild, and H. Zhang, 2021: The Earth's Energy Budget, Climate Feedbacks, and Climate Sensitivity. In Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K.

Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 923–1054, doi: 10.1017/9781009157896.009.

16. Forster, P. M., Smith, C. J., Walsh, T., Lamb, W. F., Palmer, M. D., von Schuckmann, K., Trewin, B., Allen, M., Andrew, R., Birt, A., Borger, A., Boyer, T., Broersma, J. A., Cheng, L., Dentener, F., Friedlingstein, P., Gillett, N., Gutiérrez, J. M., Gütschow, J., Hauser, M., Hall, B., Ishii, M., Jenkins, S., Lamboll, R., Lan, X., Lee, J.-Y., Morice, C., Kadow, C., Kennedy, J., Killick, R., Minx, J., Naik, V., Peters, G., Pirani, A., Pongratz, J., Ribes, A., Rogelj, J., Rosen, D., Schleussner, C.-F., Seneviratne, S., Szopa, S., Thorne, P., Rohde, R., Rojas Corradi, M., Schumacher, D., Vose, R., Zickfeld, K., Zhang, X., Masson-Delmotte, V., and Zhai, P.: Indicators of Global Climate Change 2022: Annual update of large-scale indicators of the state of the climate system and the human influence , Earth Syst. Sci. Data Discuss. [preprint], https://doi.org/10.5194/essd-2023-166, in review, 2023

17. Lee, J.-Y., J. Marotzke, G. Bala, L. Cao, S. Corti, J.P. Dunne, F. Engelbrecht, E. Fischer, J.C. Fyfe, C. Jones, A. Maycock, J. Mutemi, O. Ndiaye, S. Panickal, and T. Zhou, 2021: Future Global Climate: Scenario-Based Projections and Near-Term Information. In Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 553–672, doi: 10.1017/9781009157896.006..

Author contributions:

Conceptualization: AJ

Methodology: AJ

Investigation: AJ

Visualization: AJ

Writing – original draft: AJ

Writing – review & editing: AJ & PF

Competing interests: Authors declare that they have no competing interests.

Data and materials availability: All data used in this analysis are freely available online from the listed sources. The weighted least squares regression code is available from AJ on request.

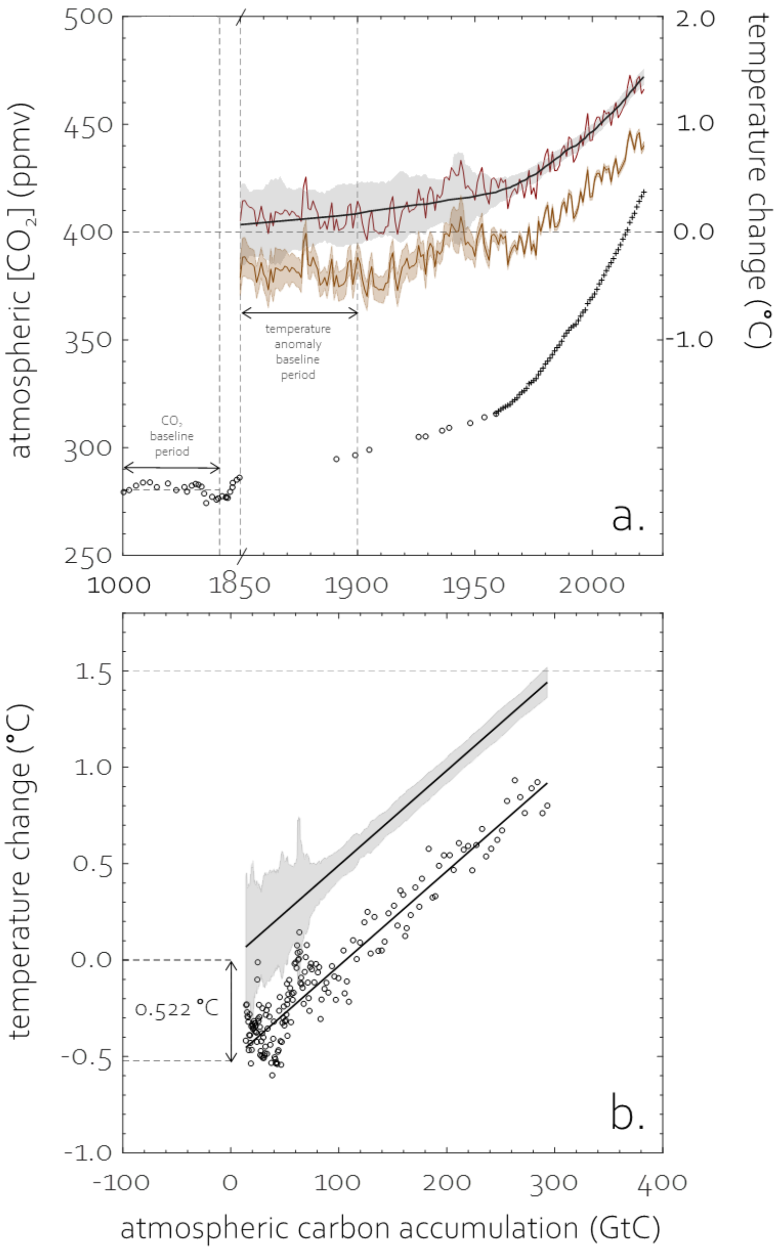

Fig. 1. a. HadCRUT5A global temperature anomaly (–; [14]), derived Global Mean Surface Temperature (GMST) change (–); expected GMST change (–), Law Dome ice core (o; [12]) and Mauna Loa direct air CO_2 (+; [13]) data. b. The relationship between the estimated atmospheric carbon accumulation (ACA) and global temperature change. Circles are for the HadCRUT5A temperature anomaly data shown in a. Lines are weighted least squares regression with and without an offset, the latter being our estimate of expected GMST change shown in a. Shaded areas are 95th percentile ranges.