How Should Multiple Temperature Time Series be Compared on Graphs?

R. W. Spencer[1]

[1]Earth System Science Center

The University of Alabama in Huntsville.

Corresponding author: roy.spencer@nsstc.uah.edu

Key Points:

- The bias adjustment for intercomparison of multiple temperature time series impacts conclusions about how global warming evolves.
- Comparison of different methods with 32 climate models shows a proposed trend-based method is superior, especially in the early years.
- The trend-based method more fully reveals the differences between models whereas other methods partially obscure those differences.

Abstract

How temperature biases in both climate models and observations are adjusted in order to make comparisons of climate change signals has been seldom discussed, yet the choice of adjustment method has a large impact on the resulting conclusions. When the primary interest is how global warming evolves through time, how the models' diagnosed equilibrium climate sensitivities (ECS) correlate with yearly temperatures is a logical test of agreement. Unlike other commonly used methods, it is shown that correlations are maximized when all of the time series are adjusted so their trend lines intersect at year zero. The issue is important to the interpretation of how climate models reveal the global warming signal over time, to how well models agree with observations, and to the policy impact and public debates regarding climate change.

Plain Language Summary

When comparing climate models to each other or to observations, the graphical representation of the data can have a large impact on visual interpretation, for instance whether observations support model estimates of global warming. It is shown that removal of model (or observational) biases with different assumed baselines impacts both the graphical presentation as well as the quantitative interpretation of model differences, especially in early years. Using global annual average temperatures as an example, when the intent is to reveal how models' evolving warming through time reflect their future warming, the superior method of baseline removal is to adjust each temperature time series so their trend lines intersect at year zero. This is recommended as the standard method by which future comparisons should be made.

1 Introduction

For over a decade there has been an ongoing, if informal, disagreement among some climate researchers regarding the proper way of using global temperature time series in the context of comparing climate model projections of warming against observations. While there has been recent progress on this using more complex methods (e.g. Craigmile & Guttorp, 2023), here we address the simple issue of how time series with roughly linear trends are commonly displayed and intercompared. In these graphs one must inevitably deal with differeing biases due to limitations and uncertainties: in models, physics and parameterizations differ, and for observations the different mix of weather stations and methods of spatial averaging and data adjustment differ. While understanding those biases is itself a legitimate research topic, here we instead address how bias offsets that are calculated and applied to the data impact meaningful qualitatve and quantitative comparison between models and/or observations. The choice of baseline can affect the answer to such questions as: Does observed warming in recent years fall well within the range of climate model projections of warming? Does the strength of a model's response to major volcanic eruption correspond to that model's long-term warming response to increasing greenhouse gas concentrations?

Here it is shown that commonly used approaches for baseline adjustment have serious limitations, and quantitative evidence is presented for a better alternative approach.

2 Time Series Comparison Using Various Baseline Removal Methods

For 32 models taking part in the sixth Coupled Model Intercomparison Project (CMIP6, Eyring et al., 2016) the global average surface air temperature (*T*sfc) between models over the 45-year period 1979-2023 varies by over 2.4 deg. C (Fig. 1a), which is large compared to expected climate change signals. To intercompare the models during this (or any) period, a common method is to remove from each model an average of multiple years, resulting in a temperature 'anomaly'. This is shown for a full-period average (Fig. 1b), an average of the first 30 years (Fig. 1c), and for only the first year, 1979 (Fig. 1d). We chose 1979 as the start year because the strength of observed global warming has been a maximum since then, as have global anthropogenic greenhouse emissions, and global satellite observations of temperature begain in 1979.

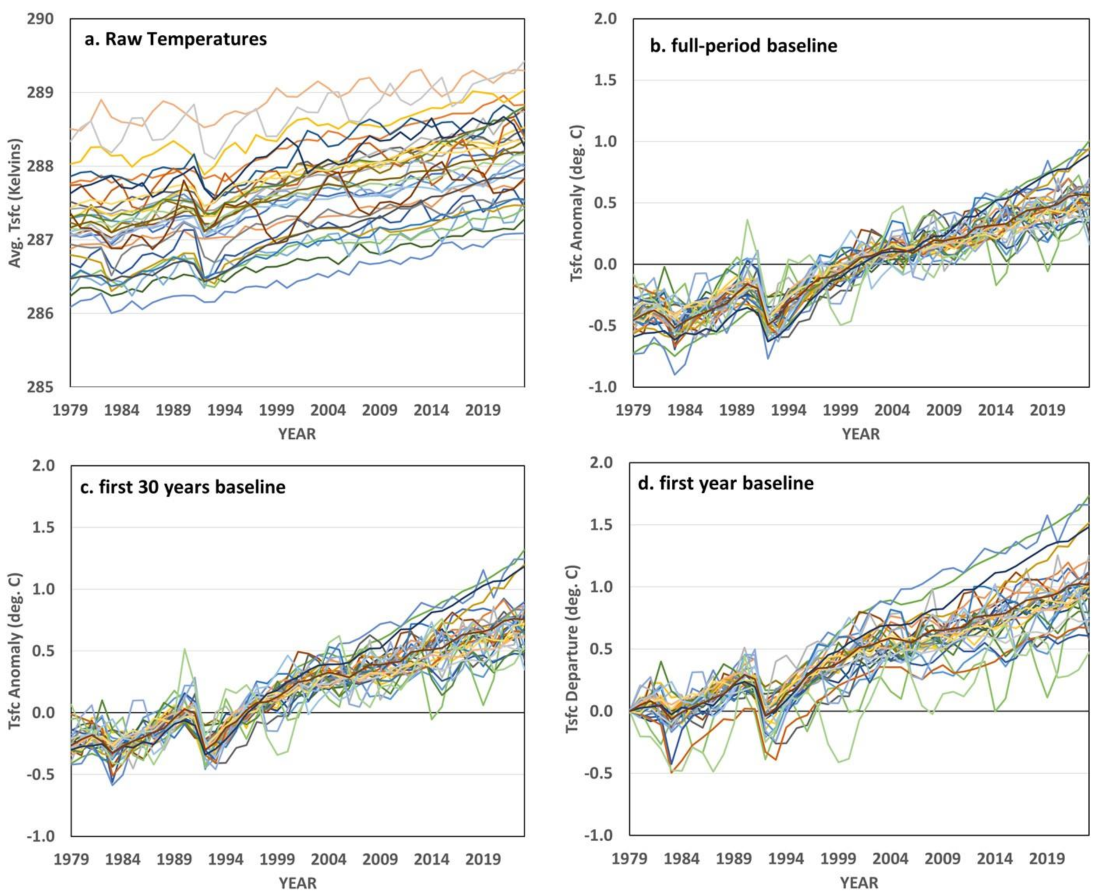

Figure 1. Annual, global average surface air temperature anomalies for 32 CMIP6 climate models displayed as (a) raw temperaures, (b) relative to the full-period average, (c) relative to the average of the first 30 years, and (d) relative to the first year.

While panels b, c and d in Fig. 1 qualitatively seem to show how warming in the different models evolves over time, a quantitative test of this is necessary. The most obvious way is to use the Equilibrium Climate Sensitivities (ECS) of those models in response to a doubling of atmospheric carbon dioxide levels above pre-Industrial levels that have been diagnosed separately (e.g. see Zelinka et al., 2020 for a model summary). If we correlate the model temperature anomalies in each year with the models' ECS values, the results in Fig. 2b reveal that models with the warmest temperature anomalies late in the record tend to have the coolest temperatures early in the record as evidenced by the generally negative correlations before 1998.

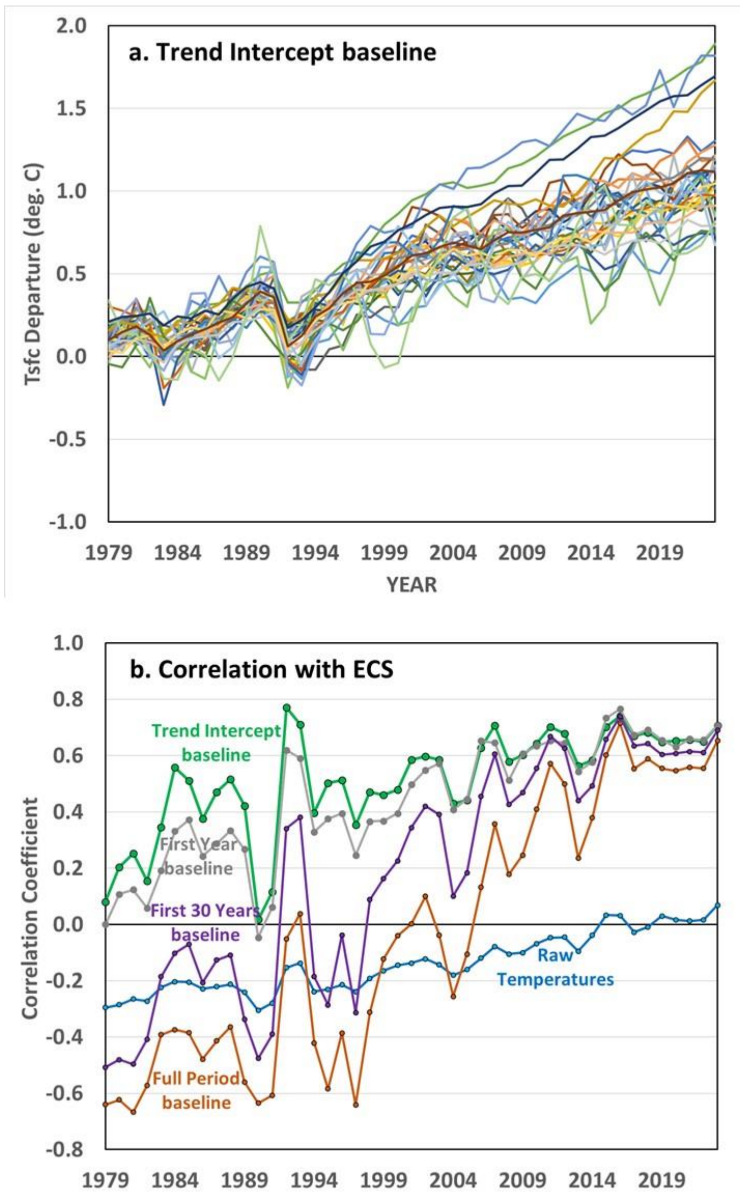

Figure 2. (a) As in Fig. 1, but after removal of the regression trend intercept relative to the first year, and (b) yearly correlation coefficients between the 32 models' ECS values and their temperature anomalies seen in the five differenct baseline removal methods represented in Fig. 1 and Fig. 2a.

This is not desirable if one wishes to compare models in individual years, or even groups of years, in terms of how warming evolves over time. In fact, any multi-year baseline period from early in the record shows this problem to some extent, that is, a tendency for the models having the most long term warming (highest ECS) to have the coolest temperature anomalies early in the record. Only using the first year (1979) as a baseline avoids this problem enirely.

But even the use of the first year as a baseline is not optimum because each climate model develops its own year-to-year internal climate "noise" due to (for example) warm El Nino or cool La Nina years. If one model is experiencing cool La Nina conditions in 1979, all subsequent years will be anomalously warm after bias adjustment using only 1979 as a baseline. Thus, a trade-off arises: Use as few years as possible early in the record to minimize the problem of models with the most warming being the coolest early in the record, but use as many years as possible to remove biases due to internal climate variability.

The most straightforward solution to this problem is to use the linear trend lines (slopes) fitted to each model time series through regression, and force all of the model time series to have their trend lines intersect in the first year. The easiest way to do this is to remove the regression intercept value from each model's time series, relative to year zero (1979). The result (Fig. 2b) shows the trend intercept method produces the highest correlations with ECS, especially in the early years. Close examination of Fig. 2a reveals the model time series with the trend intercept removed are tightly clustered in the early years, and then diverge in later years roughly in proportion to their climate sensitivities.

Note that the post-Pinatubo years of 1992-93 in Fig. 2b have a maximum correlation of all methods, with a 1992 correlation of 0.77, versus only 0.34 using the first 30 years as a baseline, and 0.62 using the first year. This shows the strength of the CMIP6 models' temperature response to the 1991 eruption of Mt. Pinatubo is well correlated with the models' climate sensitivities, but only if an appropriate baseline is subtracted from the data. This is an example of how the choice of a baseline impacts conclusions drawn from the model data.

It must be emphasized that the trend intercept method of comparing time series does not exaggerate the trend differences between the various models – the trends (linear regression-computed slopes) remain unchanged no mater how the time series are plotted. What it does is fully reveal on a graph how those trend differences evolve through time, in individual years, without obscuring the differences through forcing the most rapidly warming models to have the coolest temperatures in the early years.

3 Conclusions

Various methods have been used to compare temperature time series from climate models and observational datasets, but little attention has been given to what methods are the best for both qualitative and quantitative comparisons. While the long-term trends computed through linear regression are arguably the single best quantitative metric of the strength of global warming, the graphical relationship between various time series can be manipulated depending upon how the biases between datasets are removed. For example, this issue impacts the question of how well time series of observed temperatures fall within the envelope of many climate models' projections of temperature in recent decades. This has societal importance since it affects both public perception and policymaking which depend upon assessments of climate model accuracy.

The trend intercept method presented here most fully reveals the time evolving warming signal, especially early in a time series when the warming signal is small compared to both the size of baseline adjustments to the data and noise in the data. It is recommended that the proposed method be the standard when the goal is to fully reveal, without obscuration, the temperature differences between various climate models and observational datasets over time.

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Data Availability Statement

The CMIP6 climate model data are publicly available from the KNMI Climate Exlporer website. An Excel (Micosoft Corporation, 2018) spreadsheet with the model data and calculations used in the paper is available at https://github.com/roywspencer-nsstc/plotting

References

Craigmile, P., & Guttorp, P. (2023). Comparing CMIP6 climate model simulations of annual global mean temperatures to a new combined data product. Earth and Space Science. https://doi.org/10. 10.1029/2022EA002468

Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., & Taylor, K. E. (2016). Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. Geoscientific Model Development, 9(5), 1937–1958. https://doi.org/10.5194/gmd-9-1937-2016

Microsoft Corporation (2018). Microsoft Excel. Retrieved from https://office.microsoft.com/excel [Software].

Zelinka, M., Myers, T., Mccoy, D., Po-Chedley, S., Caldwell, P., Ceppi, P., Klein, S., Taylor, K. (2020). Causes of Higher Climate Sensitivity in CMIP6 Models. Geophysical Research Letters, 47. https://doi.org/10.1029/2019GL085782