Sensitivity to factors underlying the hiatus

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What is the hiatus?

Recent trends in global mean surface air temperature fall outside the 90% range predicted by models using the CMIP5 forcings and scenarios (Fyfe and Gillett 2014); this recent period of muted warming is dubbed the "hiatus". The hiatus has attracted broad attention in both the popular press and the scientific literature (Boykoff 2014; Hawkins et al. 2014), primarily because of its perceived implications for understanding long-term trends (Lewis and Curry 2014; Otto et al. 2013). Many hypotheses have been offered to explain the warming slowdown during the hiatus, and comprehensive studies of this period across multiple variables and spatial scales will likely improve our understanding of the physical mechanisms driving global temperature change and variability.

We argue, however, that decadal temperature trends *by themselves* are unlikely to constrain future trajectories of global mean temperature and that the hiatus does not significantly revise our understanding of overall climate sensitivity. Instead, we demonstrate that, because of the poorly constrained nature of the hiatus, model-observation disagreements over this period may be resolvable via uncertainties in the observations, modeled internal variability, forcing estimates, or (more likely) some combination of all three factors. We define the hiatus interval as 1998–2012, endpoints judiciously chosen to minimize observed warming by including the large 1998 El Niño event and excluding 2014, an exceptionally warm year. Such choices are fundamentally subjective and cannot be considered "random", so any probabilistic statements regarding the likelihood of this occurring need to be made carefully. Using this definition, the observed global temperature trend estimates from four datasets fall outside the 5–95% interval predicted by the CMIP5 models (Figure 1a). Here we explore some of the plausible explanations for this discrepancy, and show that no unique explanation is likely to fully account for the hiatus.

Is the hiatus an artifact of biases in the observations?

The horizontal lines in Figure 1a show the 1998–2012 surface temperature trend in four different observational datasets. The left-most vertical bar shows the 5–95% confidence range for the trends in the individual CMIP5 historical simulations, each of which have been extended to 2012 using the relevant RCP8.5 simulation. The observational trends for the HadCRUT4 (Morice et al. 2012), GISTEMP (Hansen et al. 2010), NCDC (Karl et al. 2015) and Cowtan and Way (2014) datasets lie well below this range, but if uncertainty in the trend is included, there is some overlap. Recent improved accounting for various biases in land and ocean temperature measurements have increased trends over those initially estimated, and corrections for Arctic coverage bias increase them further (Cowtan and Way 2014; Simmons and Poli 2014). Accounting for known observational biases has revised global mean surface temperature trends upward in recent years, reducing the magnitude of the apparent anomaly that was seen with previous versions of the products (i.e., HadCRUT3).

Is the trend uncertain due to the short time period?

Fifteen years is a relatively short time period. We might therefore expect large uncertainties in 1998-2012 global mean surface

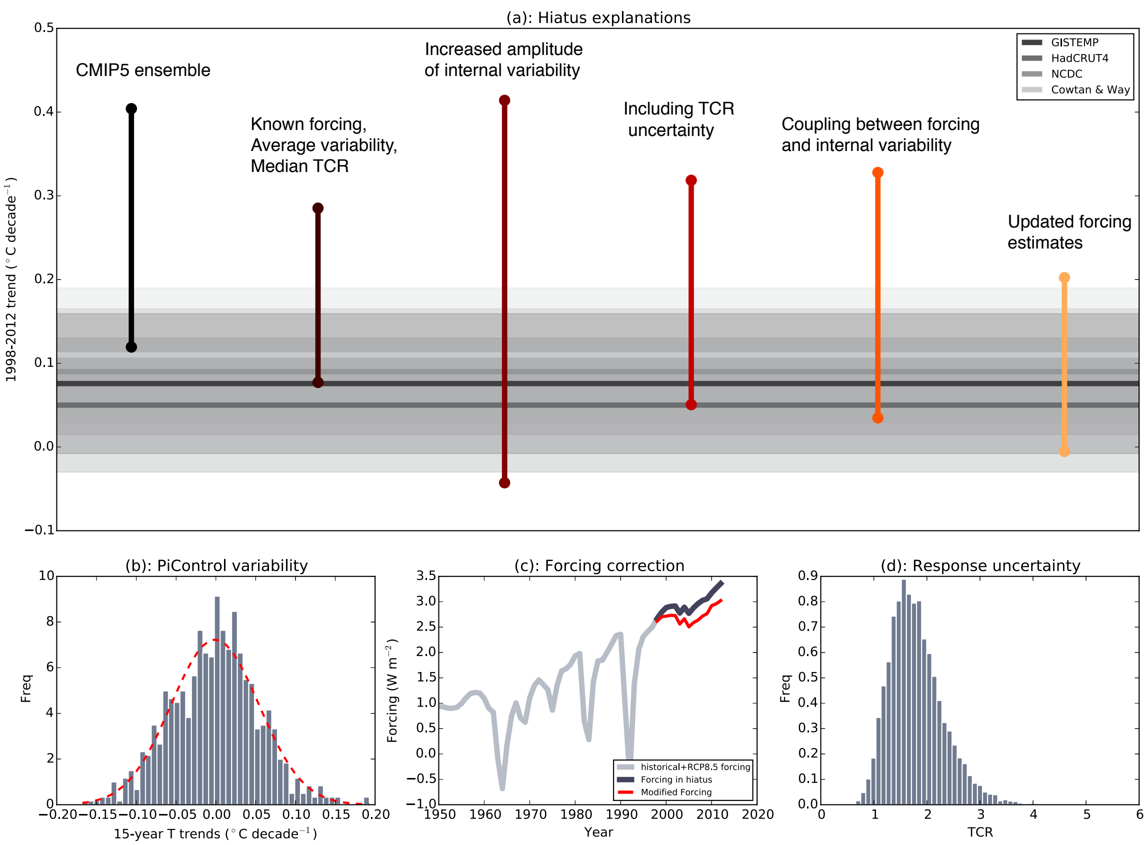

Figure 1: a) Estimates of 1998–2012 global mean surface temperature trends. Each vertical line derives from a different estimate (from left-to-right): i) the CMIP5 ensemble; ii) a theoretical estimate assuming known forcing (from the GISS-E2-R historical simulations), median TCR, and average model internal variability; iii) as (ii) but with an augmented internal variability; iv) as (ii) but with transient climate response (TCR) uncertainty; v) as (ii) but with a strong coupling between the forcing and internal variability; vi) as (ii) but with updated forcing estimates, assuming unit efficacy for each forcing.. Horizontal lines are the observational estimates from four data products, and the horizontal gray bands show the 5–95% confidence interval on the regression slope of each observational dataset over the hiatus period. b) Histogram of piControl variability in 15-year trends. c) Forcing timeseries from the GISS-E2-R historical simulations (gray and black lines) and an update based on more recent analyses (red line). d) Distribution of TCR uncertainty.

temperature trends calculated using annual-average, global-average temperatures due to the short length of the record. The shaded regions in Figure 1a show the 5–95% confidence interval on the regression slope of each observational dataset over the hiatus period, assuming no adjustment for autocorrelation in the residuals. Each of these regions overlaps the CMIP5 90% confidence interval, indicating that the uncertainties in the observed trend for 1998-2012 are one plausible scenario for explaining the divergence with the CMIP5 model trends.

Is the hiatus compatible with model-estimated internal variability?

The observed global temperature trend may simply be attributable to a particular realization of a mode (or modes) of internal variability (Huber and Knutti 2014; Marotzke and Forster 2015; Meehl et al. 2014; Roberts et al. 2015; Watanabe et al. 2014). We do not expect free-running coupled models to simulate this exact realization; a model may produce hiatus-like trends, but the chances of doing so over the period 1998–2012 are very small. Moreover, the CMIP5 models over 1998–2012 do not constitute perfect ensembles designed to incorporate all possible manifestations of internal variability. Arguably, the far longer CMIP5 preindustrial control (piControl) simulations provide a more comprehensive picture of internal variability. Concatenating piControl temperature anomalies from multiple models (e.g., Santer et al. 2009) yields a single time series of over 6,000 years in duration.[1] We calculate 15-year overlapping trends in this long concatenated time series and obtain a probability distribution of trends (Figure 1b). The width σ_c=0.06°C per decade of this distribution constitutes a reasonable estimate of the CMIP5 model ensemble internal variability, or noise.[2] For individual models, the width ranges from 0.04°C to 0.14°C per decade.

Suppose that all model climates experienced identical radiative forcing, which we will approximate using the RF time series for the GISS model (Figure 1c).[3] Suppose, moreover, that every model has the same transient climate response (TCR) to 2xCO_2 of 1.8°C (the CMIP5 multimodel mean). In this case, every model would experience an identical temperature response to forcing, and any intermodel differences would be attributable to internal variability. To approximate this "model average internal variability," we add to samples drawn from a distribution, where μ=0 and σ_c is drawn from concatenated piControl runs to the expected forced change. The resulting 5–95% interval (second vertical line in Figure 1a) appears different from the forced CMIP5 trends, due to unknown differences in forcing (not all models used the same forcings as GISS), known differences in response (TCR varies across models), and the presence of specific manifestations of internal variability such as ENSO or the Pacific Decadal Oscillation (PDO) in the historical CMIP5 models. However, given this "best-guess" forcing and response, the observed trend overlaps the 90% confidence interval produced by internal variability alone.

Do models underestimate the amplitude of internal variability?

It is possible that the 1998–2012 global mean surface temperature trend results from some mode of internal variability that is poorly simulated by the models. CMIP5 models may collectively underestimate the amplitude of internal variability such that the σ_c obtained from the concatenated control runs is an underestimate of the true internal variability. If we calculate the 15-year trend distribution on a model-by-model basis, we find that the GFDL-CM3 model has the largest standard deviation (i.e., the widest trend distribution) with σ_{GFDL}= 0.14°C per decade. Replacing σ_c with the larger σ_{GFDL} expands the 90% confidence interval such that the observed trend is comfortably within the nominal model spread (third vertical line in figure 1a). Here, we assume that the short term climate results from the superposition of a forced trend and white noise. There are of course other statistical models one could use (red noise, ARMA etc.) which would result in a larger spread in internal variability; the white noise assumption is therefore a conservative one.

Are model responses too strong?

Due to differences in climate feedbacks, CMIP5 models exhibit different values of TCR. The 5–95% confidence interval given by the IPCC is 1.0–2.5°C, with a best-guess value of 1.8°C. Several recent papers have argued that current temperature trends necessitate a revision of this range downward; however, other work has highlighted the need to consider the different efficacies of various forcing agents affecting temperature over the historical period (Hansen et al. 2005; Kummer and Dessler 2014; Shindell 2014). Given identical forcing and uniform internal variability, we draw TCR samples from a lognormal distribution with 5–95% range 1.0-2.5°C (Figure 1d) and recalculate the confidence interval for model 1998–2012 trends. Once again, the observed trend lies within the 90% confidence interval (fourth vertical line in Figure 1a).

[1] Only the first 200 years of each model control run are used here to prevent assigning undue weight to models with long control runs.

[2] This estimate is likely biased slightly high because of the concatenation and residual drift in the control runs.

[3] This is the only complete forcing time series as seen by any of the CMIP5 models (Miller et al. 2014).

Is the hiatus caused by externally forced changes to internal variability?

External forcing may couple to internal variability, changing the amplitude or frequency of known modes such as ENSO (Cai et al. 2014, 2015). For example, it has been posited that the observed widening of the tropical belt is partially attributable to a reversal of the PDO, aided by aerosol-forced changes to sea surface temperatures (Allen et al. 2014). In the piControl simulations, the distribution of 15-year trends are centered around zero; there is no a priori reason for positive or negative trends to be more or less likely. However, any interaction between forcings and internal variability may shift the trend distribution, for instance, making lower 15-year trends more likely and higher 15-year trends less likely. In Figure 1a (fifth vertical line), we demonstrate the impact on the distribution of a shift of the "noise" mean by a factor of σ_c is roughly equivalent to assuming that negative trends are favored 5 to 1 over positive trends (or vice versa).

Does the hiatus result from errors in the forcing?

It is difficult to precisely calculate forcing uncertainty across the multi-model archive, as few modeling groups specified the radiative forcings used in their historical simulations, and they are not provided as standard CMIP5 output. However, the CMIP5 experimental design has known errors in the forcings used. All CMIP5 historical experiments end in 2005, after which simulations are extended through 2012 by splicing with RCP experiments (we use RCP8.5 here). These future projection experiments contain no volcanic aerosol loading beyond 2000 (Santer et al. 2014) and use projected updates to solar output or tropospheric aerosols that did not exactly match the real world after 2005 (Huber and Knutti 2014; Kaufmann et al. 2011). Estimates of the net effect suggest that the real world had more negative forcings than projected (Schmidt et al. 2014). Updating the forcing (Figure 1c), but holding TCR and noise parameters constant, we find that reduced forcing can also reconcile observed and modeled temperature trends over the hiatus period (last vertical line in Figure 1a).

Moving forward

Evidently, if the hiatus is defined solely as a short-term temperature trend, there are many possible ways to reconcile models and observations. We suggest that, moving forward, it is more useful to focus on regional or seasonal characteristics of the hiatus mechanisms (e.g., Kosaka and Xie 2013; Trenberth et al. 2014), such as ocean heat uptake (Meehl et al. 2011), or signatures across non-temperature variables (England et al. 2014). This is because attribution of climate variability is fundamentally a signal-to-noise problem, regardless of whether the drivers are external or associated with internal modes of variability. Detection and attribution studies have established that a deep understanding of underlying physical processes can lead to detailed and complex "fingerprints" of any driver. Multiple coherent, physically expected processes may result in a stronger signal and, moreover, yield a pattern substantially different from leading modes of natural variability, increasing the strength of the signal. Additionally, complex fingerprints will distinguish processes that will not be apparent in a single short-term trend in a single variable. Studying the hiatus may not tell us much about future climate trajectories, but if we can move beyond global mean temperature to a more complete understanding of current climate conditions, internal variability, and the physical mechanisms underlying decadal fluctuations in temperature, it will be worth the time spent.

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