Assessing the consistency between short-term global temperature trends in observations and climate model projections

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Abstract

Assessing the consistency between short-term global temperature trends in observations and climate model projections is a challenging problem. While climate models capture many processes governing short-term climate fluctuations, they are not expected to simulate the specific timing of these somewhat random phenomena—the occurrence of which may impact the realized trend. Therefore, to assess model performance, we develop distributions of projected temperature trends from a collection of climate models running the IPCC A1B emissions scenario. We evaluate where observed trends of length 5 to 15 years fall within the distribution of model trends of the same length. We find that current trends lie near the lower limits of the model distributions, with cumulative probability-of-occurrence values typically between 5% and 20%, and probabilities below 5% not uncommon. Our results indicate cause for concern regarding the consistency between climate model projections and observed climate behavior under conditions of increasing anthropogenic greenhouse-gas emissions.

1. Background

While global warming is often described as accelerating, in fact, the rate of increase in global average surface temperatures has slowed in recent years. However, the significance of this slowdown has not been well-established as most discussions about the issue lack sufficient grounding in the full distribution of the expectations to which the observations are being compared. Recent research has begun to focus on this issue, but
has only done so in a limited scope. Easterling and Wehner [2009] determined the probability distribution for projected trends from a collection of climate models, but limited their analysis to trends of 10 years in length, while Knight et al. [2009] looked at the projected ranges for a variety of trend lengths, but from only one climate model.

Here we extend the results of previous analyses to determine the probability distribution of short-period trends in global temperature (in length from 5 to 15 years) as projected by a collection of climate models run under the Intergovernmental Panel on Climate Change (IPCC) A1B (“business-as-usual”) emissions scenario. We then evaluate where the current values of the observed trends of similar length fall within the model distributions.

2. Data and Methods

2.1 Climate Model Projections

Monthly output from 20 climate models (51 model runs) incorporated in the IPCC Fourth Assessment Report [2007] run under the IPCC’s A1B emissions scenario [Nakićenović and Swart, 2000] was obtained from Coupled Model Intercomparison Project 3 (CMIP3) [Meehl et al., 2007] database archived at the Program for Climate Model Diagnosis and Intercomparison (PCMDI) at the Lawrence Livermore National Laboratory. From these model projections, monthly global-average anomalies of surface and lower troposphere temperature were developed (see Auxiliary Material).
The model average temperature trend is very consistent for all trend lengths within the first two decades of the 21st century but begins to increase in the decades immediately thereafter. We therefore limit our analysis to the period January 2001 through December 2020 and consider this period to represent the expected behavior of the observed global average temperature during the first two decades of the 21st century.

Since the model runs contain internal (random) climate variability in addition to a response to the prescribed changes in radiative forcing, trends in model projections cannot be expected to match trends in observations over relatively short time spans—a few years to a decade or two. However, climate models do capture many characteristics of the primary processes driving short-term variability [IPCC, 2007, Chapter 8]. Therefore, the distribution of short-term temperature trends (of all lengths) from model projections should with high probability encompass the trends (of similar length) in the observed data if the model projections are accurately capturing climate behavior. While the observed trend falling within the model distribution of trends is not conclusive proof of the validity of climate model projections, it does serve as a necessary condition.

We develop the distributions of projected short-term temperature trends both for the surface and the lower troposphere. Through each individual model run, we calculate the moving linear trends through the first 20 years of monthly projections for time periods with lengths ranging from 5 years (60 months) to 15 years (180 months). For each model run, we develop the set of all available trends of each length. For example, for 5-year trends, we calculate the trend for the period January 2001-December 2005, February
2001-January 2006, March 2001-February 2006, successively stepping one month at a
time thorough all 60-month periods and ending with January 2016-December 2020. The
total number of trends determined from each model run declines with the increasing trend
length, from 180 5-year trends, to 60 15-year trends. For each trend length, we then
combine the set of trends calculated from each of the 51 model runs—weighted to
produce an equal contribution from each climate model (regardless of the number of
available runs)—into a single distribution representing a sample of the overall population
of potential realities contained in the collection of climate models [Annan and
Hargreaves, 2010]. Weighting each model run equally does not materially affect our
results. The distribution of 5-yr trends contains contributions from 9,180 (180 x 51)
elements, a number which declines to 3,060 for 15-yr trends (60 x 51). However, all
individual elements are not independent of each other as the moving trends within a
single model run are to some degree correlated.

2.2 Observed Temperature Record

We use observed records of global average surface temperature anomalies compiled
monthly by the Climate Research Unit of the University of East Anglia and the Hadley
Centre (HadCRU) [Brohan et al., 2006], by the Goddard Institute for Space Studies
(GISS) [Hansen et al., 2006] and by the National Climatic Data Center (NCDC) [Smith et
al., 2008]. Additionally we use observed records of global average lower troposphere
temperatures measured by Microwave Sounder Units (MSU) aboard satellites as
From the observed global temperature anomalies in each dataset, we calculate the linear trends using simple least squares regression of lengths 5 years (60 months) to 15 years (180 months) ending with the most recent data available (December 2009) (see Auxiliary Table 1 for the observed trend values).

Observed trends of length greater than 9 years include data from a period of time prior to the IPCC AR4 climate model projections (which generally begin in January 2001). However, the rate of increase of radiative forcing from anthropogenic emissions changes very little between the mid-1990s and the first few decades of the 21st century under the A1B emissions scenario [IPCC, 2007] so a comparison between observed behavior over the past 15 years and the model expected behavior during the period 2001-2020 is appropriate. We do not extend our analysis into trends of length greater than 15 years as the observed trend begins to be influenced by the 1991 eruption of Mt. Pinatubo—a type of natural forcing not included in the A1B emissions scenario.

3. Results and Discussion

There are several options to assess the cumulative probability of a particular trend value within the model distributions of projected trends. For instance, the cumulative probability of a 10-yr trend in global average surface temperatures with a value less than
or equal to zero can be determined directly from the elements of the distribution of model
projected 10-yr trends by using ranked percentiles (which yields a cumulative probability
of 6.3%), by using Student’s t-distribution conservatively with 31 degrees of freedom
representing the weighted combination of the 51 model runs (which yields a cumulative
probability of 8.4%), or by fitting a normal distribution (which yields a cumulative
probability of 7.9%). The results of these three solutions are very similar across all trend
lengths, indicating that the determination of the cumulative probability is not overly
sensitive to the choice of method. As such, subsequently we will only report the results
using the assumption of normality.

These results in the previous example can be compared with other assessments of model
trend probabilities. Easterling and Wehner [2009] used a similar statistical methodology,
but used model projections from the SRES A2 scenario to determine the probability of a
10-yr trend less than or equal to zero. They reported a probability of “about 10%” for
such an occurrence during the first half of the 21st century. This value is slightly greater
than the value from our methodology, mostly likely, because the A2 scenario examined
by Easterling and Wehner [2009] includes less forcing during the first half of the 21st
century than does the A1B scenario we used. Knight et al. [2009] examined variability
within the trends produced by the HadCM3 climate model when run under a variety of
emissions scenarios and model settings. Knight et al. [2009] found that a 10-yr trend falls
just inside the 90% range of trends produced by the HadCM3 model—a value apparently
similar to ours.
In Figure 1 we present a general depiction of the model probability distributions for trends of length 5 to 15 years for surface temperatures. As the length of the trend increases, the probably range tightens. This general solution can be used to assess the model-based probability of any and all short-term trends within the first 20 years of the 21st century. For example, the probability of a trend in global average temperatures that is less than or equal to zero becomes 5% or less at a length of about 11 years (132 months). The probability distributions for the projected trends in the lower troposphere are very similar (see Auxiliary Figure 1). The average model projected trend in the lower troposphere is about 20% larger than the surface (0.025°C/yr vs. 0.020°C/yr) and the spread about the mean is slightly larger as well.

The spread of the distributions of model projected trends is governed both by statistical uncertainty about the best-fit linear trend that results from random variability that is independent from month-to-month, as well as by the influence of random (over the longer-term) low-frequency variability that is correlated over times scales of months to decades and which may alter the value of the short-term trends for an extended time period. Our working hypothesis is that these random processes operate to influence model trends to the same degree as they do observed trends. Therefore, we assume that the model trend distributions represent the spread of potential realities (including these uncertainties), of which the single realization of the observed trend is a member.

One notable exception to this assumption concerns the true observational errors, such as those arising from incomplete spatial coverage, station number changes, and non-
climatological influences on the temperature measurements. These errors do not occur in
the model projections for which the temperature is precisely known. Estimates of the size
of observational errors are available for each observed dataset and we incorporate them
into Monte Carlo simulations to ascertain their influence on variability of trends ranging
from 5 to 15 years in length. We add this variability to the variability in the model trend
distributions (see Auxiliary Material). This results in a slight broadening of the
distributions.

From these adjusted distributions, derived separately for the surface and the lower
troposphere, we determine the cumulative probably of occurrence of the value of the
observed trend (ending in December 2009) ranging in length from 5 to 15 years in each
of the five observed datasets—three compilations of surface temperatures and two
compilations of lower tropospheric temperatures (Figure 2).

The cumulative probabilities of the observed trend values typically are less than 20%
(with the exception of GISS dataset). In all datasets the cumulative occurrence
probability of the current 8-yr trend is about 10% or less, and in all datasets except the
GISS dataset, there is less than a 10% probability of current values for trends of 7, 8, 9,
12, and 13 years in length. The values for these same trend lengths from some datasets
fall beneath the 5% cumulative probability indicating an expectation of occurrence of less
than 1 in 20 (a typical measure of statistical significance). In general, the cumulative
probabilities of the observed trends are lower for the lower troposphere than for the
surface.
4. Conclusions

For most observational datasets of global average temperature, the trends from length 5 to 15 years lie along the lower tails of the probability distributions from the collection of climate model projections under the SRES A1B emissions scenario. Typically the probability of occurrence of the observed trend values lies between 5% and 20%, depending on the dataset and the trend length. In the HadCRU, RSS, and UAH observed datasets, the current value of trends of length 8, 12, and 13 years is expected from the models to occur with a probability of less than 1 in 20. Taken together, our results raise concern about the consistency between the observed evolution of global temperatures in recent years and the climate model projections of that evolution.

Possible reasons for why current trends are unusual when set among model projections include unknown errors in the observational temperature record, differences in the true vs. A1B-defined anthropogenic forcing changes, insufficiencies of the climate models to accurately replicate the characteristics of natural variability, inaccuracies in climate model transient climate evolution, and the overestimation by climate models of the actual climate sensitivity. These are in addition to the possibility that current trends represent simply a rare but not impossible situation that is generally captured by the climate models.
As global emissions of carbon dioxide—the primary anthropogenic climate forcing agent—have been increasing during recent years at a rate similar to that specified in the A1B scenario [Nakićenović and Swart, 2000; EIA, 2008], it is unlikely that the difference between observed and projected trends arises from a significant underestimate of the changes in climate forcing prescribed by the A1B scenario. Similarly, while there are clearly differences among the observed trend values derived from the various observational datasets, all trends through the observed data fall in the lower tails of model projections, so it is unlikely that errors in the observations (which may include a warming bias in surface observations in recent years, [e.g., McKitrick and Michaels, 2007; Klotzbach et al., 2009] are the primary cause of the observed/projected differences. This leads to the conclusion that a large part of the differences between the observed trends and model-projected trends lies with the internal workings of the models. This conclusion is supported by results which indicate that natural variations in ocean/atmospheric circulation patterns are in part responsible for the recent slowdown in the rate of global temperature rise [Keenlyside et al., 2008; Swanson and Tsonis, 2009] and that inadequately-modeled decadal-scale variations in stratospheric water vapor have a significant influence on global temperature trends, including contributing to a reduced trend in recent years [Solomon et al., 2010]. Further, some results indicate that the model determinations of climate sensitivity may be too large [e.g., Wyant et al., 2006; Spencer and Braswell, 2008]. It can also be noted that the discrepancy between observed trends and projected trends is greater for satellite than surface observations.
Our results stand in contrast to results such as Rahmstorf et al. [2007] which concluded that observed trends through global average temperatures are increasing at a rate near the upper end of the IPCC projected range. The primary reasons for the contrasting conclusions are that our analysis is based upon updated climate model runs, more recent observed data, and a more comprehensive analysis of model projections.

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Figure Captions

Figure 1. Cumulative probability distribution of trend values for trends ranging in length from 5 to 15 years derived from 20 models under SRES A1B for the period January 2001 through December 2020 for global average surface temperatures. The 95% confidence range is shaded in grey and a zero trend is indicated by the horizontal black line.

Figure 2. Cumulative probabilities of the current observed values of the trends ranging in length from 5 to 15 years (each ending in December 2009) through average global surface temperature anomalies and lower troposphere temperature anomalies as complied within five observed temperature datasets.
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