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To inform processes of policy development and implementation, climate change research needs to focus on improving the prediction of those variables that are most relevant to economic, social, and environmental effects. In turn, the greenhouse gas and atmospheric aerosol assumptions underlying climate analysis need to be related to the economic, technological, and political forces that drive emissions, and to the results of international agreements and mitigation. Further, assessments of possible societal and ecosystem impacts, and analysis of mitigation strategies, need to be based on realistic evaluation of the uncertainties of climate science.

This report is one of a series intended to communicate research results and improve public understanding of climate issues, thereby contributing to informed debate about the climate issue, the uncertainties, and the economic and social implications of policy alternatives. Titles in the Report Series to date are listed on the inside back cover.

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How to Think About Human Influence on Climate

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We present a pedagogical paper on the detection of climate change and its attribution to anthropogenic influences. We attempt to separate the key thought processes and tools that are used when making qualitative statements about the level of human influence on climate.

Is the climate changing? And if so, are we causing it? These two simple questions raise some of the most contentious and complicated topics in the whole climate change debate: the detection and attribution of change. Because this is a complex topic it may help to start with a more familiar problem. Suppose you step onto your bathroom scale some morning, and look down to find the number is one pound higher than you expected. You then call out, “Honey, I’m gaining weight. I’ve been eating too much!” Here is a statement about detection and attribution, but in another context. What does it take to reach such a conclusion with any confidence?

First, how do you know your weight is actually higher? You may suspect that the accuracy of your bathroom scale is not that great: you only paid \$19.95 for it. You have also observed that readings on your health club scale differ from those at home. So there is error in the measurement itself: you can “detect” your weight increase only with some probability. Thus informed, you might say, “There is a 90% probability that my weight is between 0.8 and 1.2 pounds higher than the last time I looked!”

Second, does this measurement indicate a trend that might have some cause, like eating too much? Here another complexity enters: your body weight may go up and down by amounts comparable to your observed gain this day, regardless of what you eat, in response to changes in temperature and humidity, your psychological state (your boss is on vacation for the month), or your level of physical activity. If the magnitude of this natural variability is similar to the change you are seeing on the bathroom scale, you should be cautious when saying that you have detected something significant. You have a problem of sorting the “signal” of a significant change in your body, perhaps attributable to food intake, from the “noise” of its natural fluctuations. So a still more accurate statement might be, “There is a 70% probability that my weight has gone up between 0.8 and 1.2 pounds for some reason other than natural variability.”

The third question that arises is, why the apparent change? Weight gain does have a basis in physiology, and this knowledge may be supported by past experience and observation of others. But the relationship cannot be stated precisely because it depends on many factors, such as

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adjustments in metabolism and amount of physical activity that are poorly understood. This gives rise to a fourth question, how accurately have you recorded or recalled your food intake, physical activity level, and other factors which you know affect your weight? In this circumstance, the most that can be said with scientific accuracy about attribution may be something like, “There is a 90% chance that at least 1/2 of the increase shown on this scale is due to my eating too much.” Or, where formal analysis is missing, “Honey, the preponderance of the evidence suggests that I’m eating too much.”

To summarize, four elements are involved in this example of detection of weight gain and its attribution to increased food intake.

1. An estimate of the weight change and the error in measuring it,
2. Knowledge of the natural variability in your body weight,
3. An understanding of the mechanisms by which body weight responds to food intake and other factors, and a model of the relationship, and
4. A record of food intake and its uncertainty.

Now we shift our attention to the global climate system and our (imperfect) measurements of how climate has changed over the past century or so, our (limited) understanding of patterns of natural climate variability, our (as yet incomplete) models of the interacting chemistry, physics, and biology of the global system, and our (inaccurate) inventory of past climate forcings. The issue of *detection* concerns the ability to say with confidence that we have seen some trend, and not just the natural variability of climate. This task involves measurement of climate variables like temperature, which are analogous to the reading on your bathroom scale, and analysis of the natural variability of the system, analogous to your natural weight fluctuation. *Attribution* requires showing that any change is associated with human-induced factors and not with some other cause. This additional task requires a model of the climate system and its various influences, analogous to that for human physiology, and also estimates of factors affecting the climate system, like increasing concentrations of greenhouse gases. It is well known that these concentrations have been rising due to increased human emissions, akin to your record of food intake.

The key steps for detecting change and deciding how much to attribute to human influence can be illustrated using **Figure 1**. In the top panel is a temperature record for the globe for the past 150 years (the thin line) shown as deviations from the average temperature of 1961-1990. The early years are mostly negative and the latter years show positive deviations, suggesting a trend over time. The thick line in this panel shows an attempt by one climate model to simulate what the past 150 years would have been like taking account of only the natural influences. It shows deviations from the average, but no obvious trend. On first look, then, the analysis suggests that something other than the natural processes represented in the model was involved

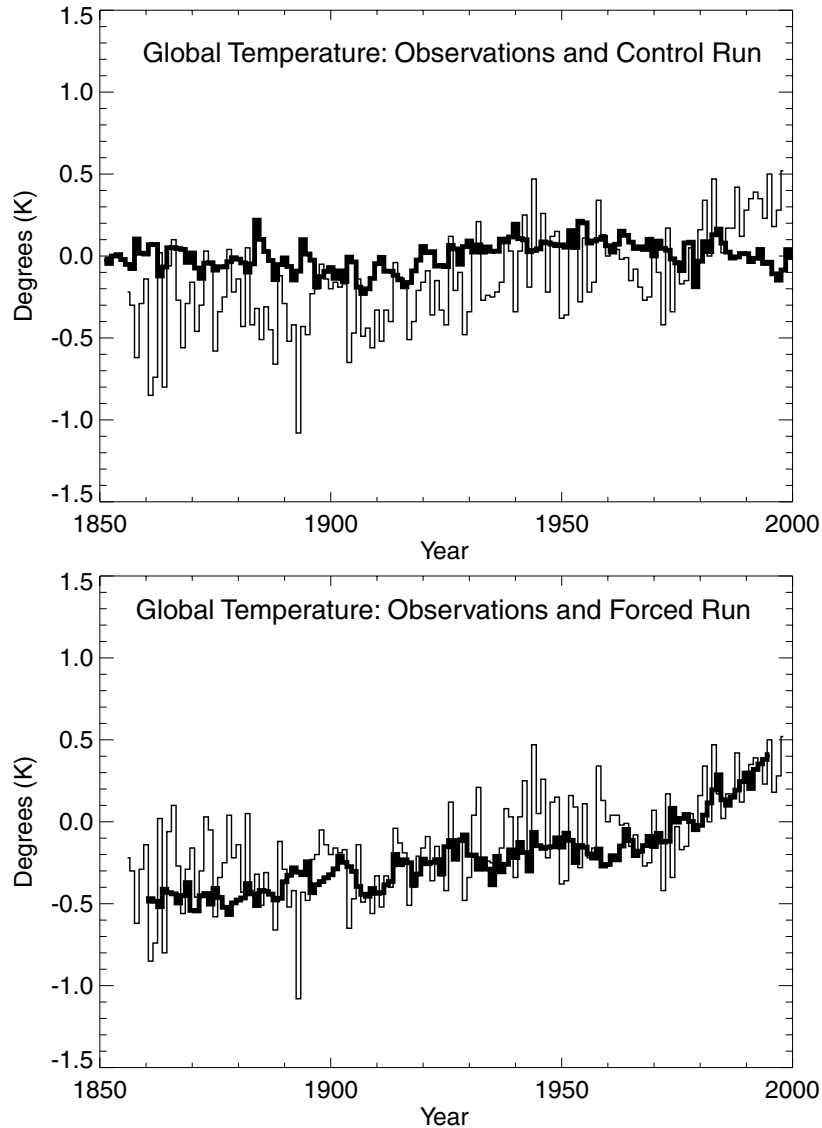


Figure 1. Top: *Simulated global-mean annual-mean surface air temperature (thick line) from a climate model simulation with no applied forcings superimposed on the record of observed temperature change for 1860-1999 (thin line, after Parker et al., 1994). The variations of annual-mean, global-mean surface air temperature are generated by the climate model's internal feedbacks as determined by the dynamics of the various components of the climate system. Bottom: As in the top figure but with the response of the climate model (thick line) to anthropogenic forcings (for one possible choice of the climate sensitivity, rate of ocean heat uptake, and net aerosol forcing) that matches the observations well (thin line).*

in determining climate over this period. The heavy line in the bottom panel is a result from the same climate model, now simulated with known concentrations of greenhouse gases (a warming influence) and estimates of human-caused aerosols (a cooling influence). The general pattern of simulated climate, once these changes are included, now fits the estimated historical record much better than that without these influences, suggesting causation. But is this causal association enough? Is there still some significant chance that the association is coincidental?

In order to be confident that the change is real, and to attribute it to human influence, we need to consider several issues. First, is the estimated global temperature record accurate? Creating the estimated record required corrections for the urban heat island effect (urban areas tend to absorb and generate heat, so thermometers there show higher temperatures than in rural areas), and for changes in instrumentation over a century. It also required estimating data for poorly covered zones, such as over oceans and Siberia. Finally, the record is more sparse the farther back in time one goes, and there is some disagreement between the surface record shown in the figure and satellite measurements (which are only available for the last couple of decades in any case). Despite these measurement issues, however, climate scientists generally agree that there has been a warming of the globe by about 0.6°C over the past 150 years (National Research Council, 2000), with some uncertainty as to the precise change.

Second, what degree of natural variation is to be expected? The climate varies over time as a result of complex interactions of phenomena involving the atmosphere, the oceans, and the terrestrial biosphere—many not captured in even the most complex climate models. These natural processes operate on time scales of a few years (El Niño and La Niña), a few decades (Arctic or North Atlantic oscillations), and some (involving deep ocean circulations) of several centuries. The temperature record shown as the thin line in Figure 1 is only a single sample of possible global behavior over a century time scale. Any other period of similar length would show different patterns, and perhaps larger fluctuations caused by the interaction of these natural processes operating at different time scales.

With such system complexity a record of 150 years is simply not long enough to allow estimation of the natural system variability. (Imagine trying to understand your own body's natural variation if you had access to a scale for only a few days.) The natural variability thus must be estimated from much longer simulations using computer models of the system, with all their shortcomings. These models necessarily must simplify a number of physical, chemical and biological phenomena, and apply rough approximations for key processes (like the behavior of clouds) where the underlying science is either poorly understood or too difficult to model. Therefore the particular forecast shown in the top of Figure 1 is uncertain, as is the model-based estimate of natural variability. The question whether the observed change is rising out of the “noise” of natural variability can only be stated probabilistically, just as with your observed weight gain.

Even if the model-based estimate of climate change were judged to exceed the estimate of natural variability with some high probability, the next question would be “why is it happening?” Can the change be attributed to anthropogenic forcings? To convincingly demonstrate a human cause is a simultaneous two-part process. First, it must be possible to reject the hypothesis that some non-human influence, such as solar variation, could have produced the same result. This is done by testing ranges of uncertainty in processes and parameters that are used in

simulations like that shown by the heavy line in the top panel of Figure 1. Second, it must be shown that the modeled effects of human factors are consistent with the observed change, revealing the so-called human “fingerprint.” Here, one must deal with yet another uncertainty.

The historical concentrations of greenhouse gases are well known, but there is large uncertainty in the estimated emissions of substances (mainly SO_x from coal-fired powerplants) that produce the cooling aerosols. Plus, the overall effect on climate of these aerosols remains uncertain. So the bottom panel of Figure 1 may reflect a lucky choice of estimates of the level of each of the modeled effects, so that they coincidentally produce agreement with the estimated historical record. For example, a different estimate of the aerosol loading, even one well within the range of uncertainty, could produce a very different simulated pattern of climate.

So how can the attribution issue be stated in a way that takes account of all these considerations? One useful way to illuminate the question is to represent explicitly the main uncertain processes in our analysis of the climate system, modeling them as a set of uncertain parameters. Then, using statistical methods and an estimate of the natural variability of the system, rule out those combinations of parameters that are inconsistent (at some level of confidence) with the historical record. What results is a map of the likelihood that different levels of temperature change would have been observed over the period, given the human forcing. This result can then be used to say, with some level of probability, that a particular fraction of the observed change has been due to human influence.

This type of “fingerprint” description can be constructed from results obtained by Forest *et al.* (2000a,b) using the climate component of the Integrated Global System Model (IGSM) developed by the MIT Joint Program on the Science and Policy of Global Change (Sokolov and Stone, 1998; Prinn *et al.*, 1999). Given an estimate of human factors affecting climate over some historical period, a single simulation of this model would yield an estimate like the one shown in the lower half of Figure 1. Fortunately, the atmosphere-ocean component of the IGSM has been designed to allow study of uncertainty in key climate processes. One is the climate sensitivity, which is a measure of feedbacks in the atmosphere which tend to multiply the effects of the direct radiative forcing by greenhouse gases. The second is a measure of the effect of ocean circulations, which determines both the rate of heat storage in the deep ocean and the rate of ocean uptake of CO₂. The historical period can be simulated many times, assuming ranges of values for these uncertain parameters. By systematically adjusting these inputs and comparing the model response with observations, standard statistical methods can be used to identify a set of simulations (corresponding to particular sets of model parameters) that are consistent with the observations at some level of confidence. Furthermore, this confidence level can be used to quantify climate-change statements equivalent to: “There is a 90% chance that at least 1/2 of the increase shown on this scale is due to my over-eating.”

Before constructing an illustrative example of this calculation, it is important to summarize the underlying assumptions:

- Our estimate of the long-term natural variability of climate is based on simulation results from the Hadley Centre's HadCM2 model (Johns *et al.* 1997). The ability to verify that such an estimate is correct remains a difficult problem.
- We apply the temperature record as if there were no measurement or sampling errors, when in fact there are.
- This illustrative example does not include the possible effects of the change of solar irradiance over the analysis period, nor do we include the well-known cooling effect of particles from volcanic eruptions.
- We assume that the estimates of the climate forcings are known with certainty, when in fact the net effect of aerosols on climate is subject to substantial uncertainty.

The possible influence of these assumptions on the results shown here will be discussed below.

We consider the observed global warming between two averaging periods: 1946-1955 to 1986-1995. Over these two periods, the observational record shows a global warming of 0.33°C . How much of this change should we think is due to human factors? The results are shown in **Figure 2**. Using the ocean-atmosphere component of the IGSM, and an estimate of anthropogenic climate forcings over this period, we have simulated the climate change over the period for the combinations of climate sensitivity and ocean response indicated by the "+" symbols in the figure. Based on these calculations, we can identify a set of the parameter combinations that are consistent with the observations at a given level of confidence, shown by different levels of shading in the figure. The completely unshaded region represents an 80% confidence interval (that is, the true values of these parameters are only 20% likely to lie outside this region, with 10% above and 10% below). Then there are three degrees of shading. Adding the light shaded area extends the confidence interval to 95%, and the middle level of shading extends it to 99%. Thus there is less than a 1% chance that the (unknown) true values of the parameters lie in the region of most rapid temperature change, the darkest region with the combination of a high sensitivity and a slow ocean.

Also shown in Figure 2 are lines that show the simulated change in global temperature over the period that results from the various parameter combinations. The observed change, 0.33°C is indicated by a dashed line, and it can be seen that this change over the 40-year period might have been the result of a high sensitivity ($S = 4^{\circ}\text{C}$) and an ocean that rapidly stores heat (fraction of warming = 0.55), or of a lower sensitivity ($S = 2.5^{\circ}\text{C}$) and an ocean that takes up heat slowly (fraction of warming = 0.15), or indeed by any other point along the dashed line. Where the limit lies as one proceeds to the northeast in the figure depends on information which is not available in this analysis.

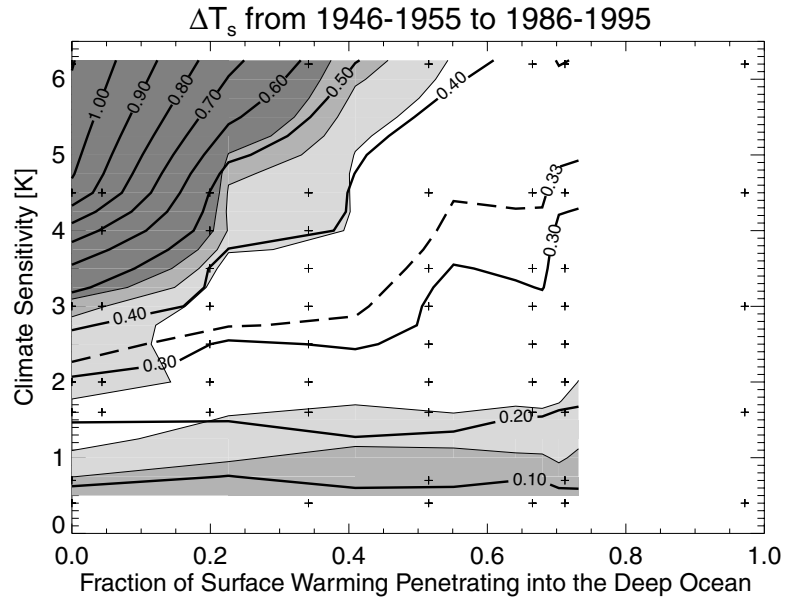


Figure 2. The dependency of modeled temperature change on two model characteristics: climate sensitivity (vertical axis) and the rate of heat uptake by the deep ocean (horizontal axis). Together, these two characteristics determine the model's response to the applied climate forcings, which, in this case, are historical changes in the concentrations of greenhouse gases, sulfate aerosols, and stratospheric ozone. The temperature change shown is the decadal mean for 1986-1995 minus that for 1946-1955. The observed change is shown by the dashed line. The shaded regions are rejected at 20%, 5%, and 1% level of significance (from light to dark respectively) as producing simulations inconsistent with observations (after Forest et al., 2000a,b). The noisiness of the temperature contours and shaded regions results from natural variability in the modeled climate change. (Here, the rate of heat uptake is measured by the fraction of surface warming which has penetrated to a depth of 580m in the ocean for a particular scenario, climate sensitivity, and time. The fraction was calculated for a scenario in which CO₂ increases 1% per year, for a climate sensitivity of 2.5 K, and at the time when the CO₂ concentration has doubled.)

Now, we come to the extraction of a statement about attribution from this analysis. Note that the 0.20°C line lies very near the lower boundary of the 80% confidence region. This means that there is only a 10% probability that the modeled effect of the human influences on climate is less than 0.20°C over the 40-year period. Put another way, there is a 90% probability that at least 0.20°C, or approximately 60% of the observed 0.33°C warming, can be attributed to the anthropogenic forcings applied to the climate model. Because of natural variations on decadal and longer timescales, this statement will vary depending on the period of record chosen. As an example, one might consider how this statement would change if the size of the confidence region (white region) were to be reduced (*i.e.*, higher confidence). In that case, the temperature contours would remain fixed and a higher fraction of the observed warming would be attributed at the 90% confidence level or the same fraction would have a higher confidence level.

So what are we led to conclude from this result? How are the four elements of the detection and attribution issue combined? First, we have used the climate model to define the relationship

between radiative climate forcings and temperature changes. Second, the strength of this response is varied systematically by alternative settings of the model parameters and results are chosen to be acceptable or unacceptable when compared with the observations. Third, the natural variability, as estimated by the HadCM2 climate model, is directly included in these comparisons to determine the confidence regions. Finally, the errors in the observations are assumed to be small when compared with the natural variability.

Each of these steps involves uncertain assumptions. For example, the uncertain strength of the aerosol forcing could alter both the acceptable region of parameters and temperature changes. Also, we have not included the possible effects of a change in the solar energy reaching the earth nor have we included the well-known cooling effect of dust particles from volcanic eruptions. Each of these effects contributes to natural variability of climate and could decrease the fraction of explained warming by our simulations by widening the range of acceptable model parameters or changing the modeled temperatures. Additionally, the HadCM2 estimate of natural variability should itself have an associated uncertainty which has not been determined. When combined, these uncertainties will alter our conclusions, and most of the components that are inadequately modeled tend to reduce the fraction of the observed warming that can be attributed to human influence with any particular level of confidence. Further, if this method were applied to models other than the MIT IGSM, somewhat different results might be obtained, reflecting the structural uncertainty among models, in contrast to the parameter uncertainty in the MIT model explored here.

It is because of these difficulties that scientists who try to summarize available knowledge about detection and attribution resort to statements such as, “the preponderance of the evidence indicates that ...,” or “it is likely that a significant (or major, or substantial) portion of the observed warming is attributable to human influence.” The words “preponderance” or “significant” or “substantial” can take on implicit probabilistic significance among scientists (for example, in the IPCC drafting groups) who spend many hours debating them, although there is evidence their meaning can vary dramatically even among technical experts in the same field unless assigned quantitative values (Morgan, 1998). They are open to almost unlimited interpretation by lay people who only have the final text (or worse, a summary of it) to go by. Our calculations illustrate one way to make these statements more precise. We hope that this analysis of what lies behind these words may help avoid the too frequent leap to one of two extreme positions: that because of the uncertainty we know nothing, or that scientists have “proven” that we are responsible for temperature changes of the recent past.

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