The Detection and Attribution of Human Influence on Climate*

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Abstract

This article describes the field of the detection and attribution of climate change and highlights recent progress, major issues, and future directions. The attribution of global temperature variations over the past century to a combination of anthropogenic and natural influences is now well established, with the anthropogenic factors dominating. Other aspects of the climate system, including regional quantities, are increasingly being found to also show a detectable signal of human influence. Of particular interest, though, is the attribution of changes in nonmeteorological quantities, such as hydrological and ecological measures, and of changes in the risk of extreme weather events to anthropogenic emissions. Methods are being developed for tackling these two problems but are still in the early stages. As the field gradually includes a service focus, the biggest challenges will become the integration of various approaches into an overall framework and the communication of the capabilities and limitations of that framework to the outside community.

Contents

1. WHY CARE ABOUT THE PAST?

The term climate change generally has a connotation of being about the future, and in particular about future warming induced by emissions of greenhouse gases by humans. Indeed, the United Nations Framework Convention on Climate Change (UNFCCC), the UN agreement coordinating international measures to tackle climate change, defined climate change as such (1). In truth, though, we not only believe that the climate has changed in the past, but we also believe a variety of factors can influence the climate, including human activities other than greenhouse gas emissions and factors completely unrelated to humans. In light of this, the most recent report of the Intergovernmental Panel on Climate Change (IPCC) assessing progress in global research of climate change, commissioned by the UNFCCC, adopted a more widespread definition of climate change (2).

What is the climate? A common definition is that it is the statistics of weather measured over some period, such as 30 years (3). This definition seems inadequate, however, both because it is purely based on measurement rather than some integral property of a system and because it implicitly denies that the climate can change. A more robust definition, used in this review, is that the climate is itself the statistical properties of possible weather, with the actual observed weather being just one realization of many possible realizations within a given climate (4).

In this light, the past has an invaluable role in illuminating our knowledge of climate change. Is future anthropogenically induced climate change still only hypothetical, or is it already being noticed? How does predicted climate change compare to the range of weather experienced in the past decades and centuries and thus to which we and ecosystems are implicitly adapted? Does evaluation of predictions of past climate change provide a constraint on predictions of future climate change? Have anthropogenic emissions altered the chance of a damaging weather event in the present, implying in certain settings that the emitters may be liable for damages (4–6). Are risk assessments in serious error if they use only past observations because the current climate differs from the climate of the past (7)?

1.1. What Is the Difficulty?

These questions may seem straightforward, and in many cases, addressing them seems straightforward too. There are, however, a number of problems. The biggest problems are that the weather varies and that we have only one sample of the weather under the climate of the recent past. The weather may seem to be changing, but is this the result of one influence or another, or is it just simply a trick arising from the inherent variability of the weather? Ideally, we would like to construct an experiment where we could rerun the weather many, many times under different scenarios of climate conditions. Alas, that is impossible, so the experiments must be conducted using models of the climate system. Models are by definition imperfect recreations of the real world, and so the results of these experiments must be interpreted with all sorts of caveats in mind.

We also do not have perfect observations of the past. Even today, our knowledge of the current weather has considerable holes; in general, the record is patchier farther in the past. Continuity of the measuring techniques, vital for determining long-term changes, is often not maintained in observational systems designed for short-term forecasting. These problems are magnified for records monitoring nonclimate systems when investigating the effect of weather on those other systems. Observational limitations also restrict our knowledge of change in the various external factors that are probably influencing the climate system. Thanks to analyses of ice cores, we think we know fairly accurately how atmospheric concentrations of well-mixed greenhouse gases have changed, but the magnitude and pattern of anthropogenic emissions of sulfates and the existence of a trend in the luminosity of Sun remain quite uncertain.

Finally, the complexity of the problem is daunting. How many different factors could conceivably influence the climate? How many different factors, other than climate change, could also be influencing an ecosystem or drainage basin? At the personal level, is the warming on my property a consequence of global emissions, or is it a consequence of the new tarmac used to repave the road or of the felling of the large oak tree?

1.2. This Review

Despite this complexity, some questions concerning the detection and attribution of climate change have already been addressed, and more will probably be addressed in the next few years. This review will now proceed with a description of the standard direct approach to the detection and attribution of climate change and of what has been achieved with it when looking at measures of the climate system (Section 2). In practice, though, we care about whether these changes are also affecting various nonmeteorological things that matter to us (Section 3). In theory, the direct approach can be used for the attribution of such impacts too, but it can be exceedingly difficult or even impossible to apply, and so an alternative indirect approach has usually been implemented. In the end, the risk of damaging weather events is often the most visible and influential aspect of climate change; research into the attribution of changes in the risk of such events is discussed in Section 4. Finally, this review will end with a discussion of challenges and developments in the field that may be expected in the next few years.

2. THE STANDARD DIRECT APPROACH

The initial tasks of detection and attribution studies were to determine if the global climate was warming and to determine the cause of any detected change. Essentially, this involves comparing output from simulations of climate models with the observed instrumental temperature record. First, is the climate changing? If it does appear to be changing, then what external forcing(s) is(are) influencing it? Straight away, we face difficulties. It is simply infeasible to include the effects of all conceivable external influences in a climate model simulation, so we have to settle for all plausibly important forcings, subjectively leaving out direct heating from hot internal combustion engines for instance.

A number of potentially important forcing candidates exist (**Figure 1**). On the natural side, the forcing could be changes in the solar luminosity or changes in the scattering of sunlight by stratospheric aerosols from explosive volcanic eruptions. On the anthropogenic side, the radiative effect of increasing concentrations of greenhouse gases is the most famous, but humans are probably affecting the climate in other ways too. Emissions from industrial and transport activities form aerosols, which can directly scatter sunlight (the direct effect) or can change the optical properties and lifetime of clouds (the indirect effects); burning of biomass emits dark aerosols, which can absorb and scatter sunlight; various types of land use result in different optical and hydrological properties of Earth's surface; and airplane exhaust can produce contrails. All of these anthropogenic and natural forcings have been changing over time: Which is the culprit? Of course, we actually expect all of them to have contributed, but in varying amounts.

There are addional limitations on what we can implement in a climate model. It is easy to vary the solar luminosity or the CO_2 concentrations, but how to implement variations in aerosol emissions is not nearly so obvious. Furthermore, although we have quite accurate measurements of historical greenhouse gas concentrations in the atmosphere, estimates of variations in the solar luminosity are derived from very indirect methods in the presatellite era, with each method yielding rather different long-term trends. Local details of changes in land surface characteristics are largely unknown over substantial areas of the planet. Minimizing these caveats remains an important area of study.

2.1. The Regression Method

In order to attribute at least some of the observed warming to variations in an individual forcing, we need to determine if the output of the climate model is consistent with the observed warming when the variations in that forcing are included and if the output is inconsistent when that forcing is excluded. A direct comparison of the model simulations under these various forcing scenarios against the observational record can be used to produce likelihood measures. In one method, these likelihoods are evaluated within a Bayesian framework to determine the support for or against scenarios and to decide the most probable scenario among them that best describes the observed changes (9, 10).

The most popular method, though, has taken advantage of two apparent properties of the way the climate system responds to an external forcing. First, at large spatial scales, the response appears to be linear to the forcing, so for instance, a model that underestimates the warming to greenhouse gases in the first half of the twentieth century will similarly underestimate the warming in the second half (8, 11). Second, the responses seem to be additive, so the sum of the responses to separate forcings is identical to the response to the sum of all of the forcings (12, 13).

With these assumptions, a simple linear regression can be used to compare the evolution of the observed record of a meteorological variable, $x_{\mathrm{OBS}}(t)$, against the evolution of that variable output from a series of climate model simulations, $x_i(t)$, (14) as follows:

$$x_{\mathrm{OBS}}(t) = \sum_i \beta_i x_i(t) + \nu(t). \qquad 1.$$

Figure 2 demonstrates this method. The regression approach can be applied only for anomalies from the full period covered by t, and not actual values. In the version shown here, t is time, but it could include spatial information too. Each $x_i(t)$ is the output from a simulation (or collection of simulations with slightly different initial weather states, to increase the signal-to-noise ratio) run under external forcing scenario i. The β_i is the regression coefficient required to attain a best fit to the observed record. For example, take the case of temperature from just one simulated scenario, in which changes in all expected major external forcings are included (ALL). If the model matches the observations nicely, then $\beta_{\mathrm{ALL}} = 1$; if there does not seem to be any match at all, then $\beta_{\mathrm{ALL}} = 0$. In practice, limited sampling of both observations and simulations means that these regression coefficients cannot be determined exactly.

The $\nu(t)$ is the residual of the regression. The goodness of fit could be estimated by comparing $\nu(t)$ against the natural internally generated variability of the climate system. Unfortunately, we do not have direct measurements of this. One possibility is to use reconstructions from measurements of proxies covering the past few millenia, but there are uncertainties about the fidelity of these reconstructions, and furthermore, natural (and even anthropogenic) external forcings varied over this time (albeit less than the overall forcing change over the past century). The most popular method has been to estimate the internal variability from climate model simulations in which all forcings are held constant. The advantages are that the experimental setup is sound and that long simulations (and thus precise estimates) are possible; the disadvantage is that the simulations are produced from models, not the real world itself.

The regression shown in Equation 1, usually termed "ordinary least squares" (OLS), has often been implemented in an "optimal detection" mode that rotates the comparison into the direction of maximum signal-to-noise (14). Other recent developments include accounting for finite sampling of the model responses $x_i(t)$ (15) and of uncertainty in the pattern of the model responses themselves (16).

2.2. What This Approach Has Told Us

Here, we provide a short illustrative summary of recent results in the detection and attribution of climate change. The reader is pointed toward References 17 and 18 for more comprehensive reviews.

Surface air temperature was the first quantity to be studied in the detection and attribution field because it is well monitored, it is well understood (and thus it appears to be accurately described by climate models), and it is the first variable to respond to most external influences (especially greenhouse gases). A landmark in the field was the study of Stott et al. (19), which showed that observed global temperature changes over the twentieth century were inconsistent with those in simulations of a fully dynamic climate model when the external forcings remained constant, when historical changes in only natural external forcings were included, and even when historical changes in only anthropogenic external forcings were included. The punchline was that the observations and the model simulations were consistent only when historical changes in both the natural and anthropogenic factors were included. This result is visible in the modern **Figure 3**, which shows raw (i.e., the data have not been put through a regression analysis) global temperatures from the observational network and simulations from multiple climate models. **Figure 4** shows what happens when the model simulation output has been adjusted according to a regression against the observations. For global mean temperature, the difference is generally small, but it can be important for regional values or for other climate variables.

The detection and attribution of the effect of anthropogenic forcings on global mean temperature is so robust that it holds even in extremely simple models of the climate system (20). It also holds at subglobal scales; in particular, the effect of anthropogenic emissions has been detected in the temperature changes over all seven continents (21, 22).

A major advantage of the regression approach is that it effectively detunes the climate models. Schwartz et al. (23) pointed out that the spread in temperature changes across climate models (**Figure 3**) is smaller than would be expected given the spread in estimates of historical changes in the external forcings (**Figure 1**), suggesting that models are tuned to work well with a chosen set of forcing estimates. In fact, this is not an issue for attribution studies, which use the regression approach, because the amplitude of the change is constrained entirely by the observational record. The pattern of change is the important input from the climate models, and response patterns tend to be robust (e.g., the response to volcanic eruptions occurs soon after the eruptions, the response to sulfate aerosols tends to follow the spatial pattern of the aerosols) and exceedingly difficult to tune.

Detection and attribution of changes in other climate variables is currently less advanced than for temperature. For instance, the temporal and latitudinal aspects of variations in global land precipitation have been found separately to be affected by volcanic eruptions and greenhouse gas emissions (24, 25), but study of the combined space and time variations have not yet detected a signal. An anthropogenic fingerprint has also been found in atmospheric circulation (26), but the amplitudes of the model estimates are inconsistent with what has been observed. Nevertheless, changes in some regional nontemperature variables are already large enough to stand out: Anthropogenic contributions have been detected in tropical Pacific atmospheric circulation (27), Arctic precipitation changes (28), and Arctic sea-ice ice extent (29), for example. A more comprehensive review is given in Reference 18.

2.3. Current Challenges

Recently, a main research focus has been to ensure that all possible sources of uncertainty are quantified. With the development of uncertainty estimates for observational products and the development of more versions of climate models, it is becoming possible to implemement more comprehensive methods. Another goal is to minimize the reliance on various assumptions in the standard approach. For large-scale temperature changes, these developments are generally syntactic, providing more accurate detail but without changing the underlying picture. For other variables, however, such issues may be substantial. Observations of precipitation, for instance, are difficult and prone to bias, so inclusion of a measurement error in analyses could be important. Meanwhile, the largely heuristic representation of precipitation processes in climate models results in important discrepancies between the models in both the response patterns to external forcings and the characteristics of the natural internally generated variability (24), so methods of evaluating these differences are vital.

With a push for more regional studies, a major question is how far the standard approach can go. Barnett et al. (30), Bhend & von Storch (31), and Bonfils et al. (32) have pioneered an approach, which uses downscaling models, to allow examination of smaller spatial and temporal scales. Nevertheless, many of the assumptions, for instance of linearity and additivity, may not hold at spatial scales smaller than continents. Most importantly, though, further important external influences may also be involved at regional and local spatial scales; because these were not included in the downscaling studies, these results demonstrated consistency but not attribution (31).

3. ATTRIBUTION OF CHANGES IN MANAGED AND NATURAL SYSTEMS

The demonstration that the climate system responds to greenhouse gas emissions (and other forcings) is, of course, not very useful information to any but the most precautionary stakeholder. What matters to the ecologist is whether the greenhouse gas emissions (or other forcing) are affecting a specific ecosystem, to the hydrologist whether the emissions are affecting runoff in a particular basin, and to the health authority whether the emissions are altering local environmental conditions. The difficulties encountered when analyzing climate variables are compounded when extending detection and attribution studies to nonclimate systems. Observational measurements of nonmeteorological quantities are very often of poorer quality than for meteorological quantities (at least in the context of long-term monitoring), the modeling has an extra layer (or more) of complexity, and the simplifying assumption of linearity can be dubious.

Some warning is required at this point. The field covered in this section is very young. It also involves disparate groups of researchers. The attribution of climate change requires only climatologists, and thus research can be effectively coordinated. Studies of attribution of changes in nonclimate systems to anthropogenic emissions requires an ecologist or hydrologist or other specialist to take the lead, depending on the system being examined. This means there is no natural arena for coordinating research, so standards and terminology differ depending on the field. In reading this discussion, therefore, it must be kept in mind that it has been written by climatologists. Also, our terminology differs from that used elsewhere. For instance, in their review, Rosenzweig et al. (33) use the term joint attribution to refer both to indirect approaches and to the end-to-end approach when confounding factors have not been considered. Because joint attribution covers many different methods and because the word "joint" has a very specific definition in the field of statistics, we have chosen not to include the term here.

3.1. Indirect Approaches

Most claims of attribution of changes to anthropogenic emissions in nonclimate systems are supported by the sequential attribution approach (**Figure 5**). This involves separating the analysis into two steps, one for changes

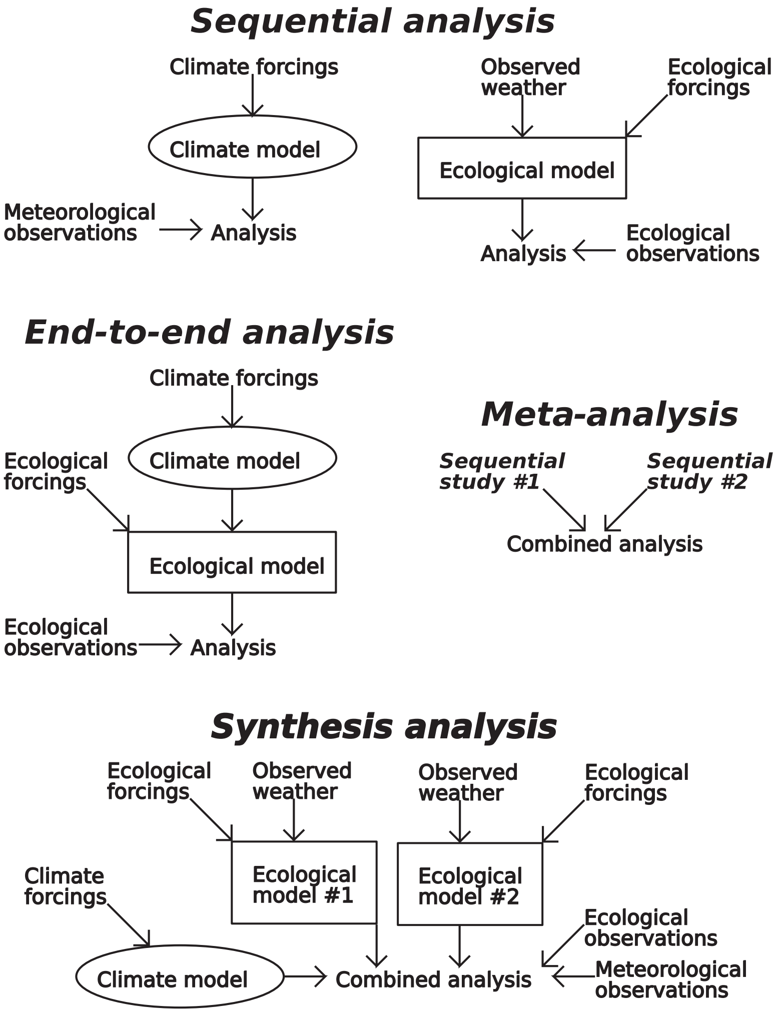

Figure 5

A schematic diagram comparing the end-to-end, sequential, meta-analysis, and synthesis approaches to attribution for an ecological system. The sequential approach differs from the end-to-end approach in having a discontinuity between the attributed climate change and the observed weather driving the ecological model. The meta-analysis approach takes results from studies of many ecological systems and takes consistency among all of these results as support for the individual results. The meta-analysis is shown here operating on results from sequential analyses but could also operate on results from end-to-end analyses. The synthesis approach compares the pattern of changes in many ecological systems to what would be expected given historical weather, and then brings the result into a sequential approach.

in a measure of the nonclimate system owing to local changes in weather and the other for regional climate change attributed to anthropogenic emissions (and/or other external forcings) (33). The catch is the discontinuity between local weather and regional climate change because uncertainty in the interface between the two levels is lost (33, 34). For instance, local factors that might influence the climate are ignored; indeed, this is a main reason that climate attribution studies have not proceeded to spatial scales much smaller than continents (31).

One way to try to minimize this problem is to include many sequential analyses in a meta-analysis (33, 35). This approach involves collecting results from sequential analyses of many different natural and/or managed systems and checking for consistency among the results (**Figure 5**). The assumption is that recent variations in other systems can serve as proxy experiments for each other. For example, if we examine a large number of ecological systems and find that the vast majority are responding in the direction expected as a result of anthropogenically forced climate change, then it can be argued that anthropogenic emissions are impacting ecological systems. The synthesis approach, by contrast, reverses the sequential and meta-analyses (35). The pattern of observed changes in the nonclimate systems is compared against what would have been expected given observed historical weather. This result is then essentially input into a sequential analysis, with the attribution of global climate change taken as the other input (**Figure 5**).

The synthesis approach has the advantage that it minimizes the importance of the missing link between attributed climate change and observed weather because the uncertainties in this link should be smallest at the global scale. The logic in this approach is still questionable though (34). For instance, it assumes that all of the natural and managed systems are responding to the same meteorological variable (usually temperature) and, furthermore, for them to be responding to local, as against nonlocal, weather. Like the meta-analysis approach, it can be used to implicate anthropogenic emissions on collective changes in natural and managed systems but not to the individual systems themselves, especially when very different types of systems are included. Does the response of a hydrological system really tell us anything about the response of an ecological system?

There is also the issue of confounding factors. Most studies have gone to great lengths to ensure that there is no bias in the selection of the nonclimate systems and that other factors, such as local land planning, would not give the same result (35). However, it is quite conceivable that multiple factors acting separately could give the same result. Ecological systems, for instance, are optimized for some historical environmental conditions. Thus, in a simplistic argument, most external disturbances of an ecological system would have a negative effect on most measures, regardless of whether the disturbance is climate change, land-use change, or pollution. The synthesis approach gets around this a bit by comparing patterns of expected and observed change. However, because the comparison of expected and observed change is binary (they are in the same direction or not), the comparison of patterns may not be that strong a test.

3.2. The End-to-End Approach

In the end, what is desired by most interested parties is direct or end-to-end attribution, where the interface between the climate and nonclimate models is explicitly modeled (34, 36), as shown schematically in **Figure 5**. Still, in most cases, local factors are so varied and uncertain that it is only possible to estimate whether observed trends in a nonclimate system appear inconsistent with stationarity and consistent with what could be expected from externally forced climate change. Although not usually framed as such, these consistency studies essentially are a comparison of likelihood estimates.

To date, we know of only two studies that have looked at consistency of an impact of anthropogenic climate forcing in an end-to-end approach. Gillett et al. (37) examined changes in the Canadian areas burned in forest fires on decadal timescales, using a statistical model of the relationship between temperatures and area burned derived from shorter timescales. Barnett et al. (30) examined changes in river flow and the fraction of precipitation remaining as snow using statistical downscaling models to convert global climate model output into a format that could then be input into a hydrological model. Nevertheless, neither study examined the possible effects of nonclimatic influences. Thus, the first true end-to-end attribution study has not yet been performed.

3.3. Current Challenges

In short, we need more end-to-end studies (34). This is not simply for the inherent usefulness of the studies themselves. They will also help interpret the results of less direct methods. For this purpose, at least some of these studies need to be thorough, including other possible nonclimatic influences; collectively, they must also span many different nonclimate systems, because what works for one type of system may not for another. One issue is that end-to-end studies require detailed models of the natural or managed systems being examined. For most nonclimate systems of interest, however, process-based models of sufficient accuracy do not yet exist. In some cases, the investment behind the development of climate models has not been reciprocated; in other cases, the system being examined does not possess fundamental equations analagous to those of fluid dynamics and radiative transfer, so the modeling framework is unclear. Currently, indirect studies usually use rather heuristic models or arguments. However, some systems appear to be very nonlinearly sensitive to external nudges, for example, with epidemiological systems capable of responding by switching between endemic and epidemic behavior (38), so heuristic arguments are not satisfactory. The confounding influence of other external forcings on both the local climate and the nonclimate system also needs to be examined more systematically.

On a larger scale, the priority is for monitoring. The UNFCCC stipulated that all parties should monitor emissions and climate but is vague on monitoring adaptation to climate change (1). Monitoring of nonclimate systems is an important issue. In general, these systems are poorly monitored—with measuring techniques that vary substantially through time. Assessments of the success of adaptation measures will not be possible without stable monitoring over the long term.

In the end, however, scientific research is only part of the issue. Stakeholders have a choice whether to require solid attribution studies or to accept more circumstantial estimates. In particular, the question must be asked whether attribution is possible in the absence, or near absence, of observations, because for most possible impacted systems historical monitoring is inadequate and will be so for some time. For example, Raxworthy et al. (39) examined changes in the altitude of reptiles and amphibians on the highest massif in Madagascar. The limitations were many and severe: Only two surveys existed, which were one decade apart; station temperatures were measured at great horizontal and vertical distance from the survey transect, and even outside the country during times of civil war; and no model existed for the distribution of these species, so an extremely simplistic model relating temperature change to upslope migration was adopted. Consequently, the study described itself as a preliminary appraisal recommending additional surveys and monitoring. However, by the time additional surveys and monitoring will provide sufficient data for a full attribution analysis, a number of the species, most endemic to Madagascar and many only found on the single massif, may already have been pushed past the massif's summit into extinction. Are we willing to risk this by keeping the bar for attribution studies so high?

4. ATTRIBUTION OF WEATHER RISK

Recent extreme meteorological events have highlighted the needed ability to address the attribution problem for such events (4, 6, 40). Quantitative information is required for the estimation of current weather risk, as estimates based on the historical record are already substantially biased in some cases (7, 41). Estimation of weather risk is also needed to inform liability assessments, whether for legal settlements (5) or for dispensing funds for adaptation activities. Finally, statements of the connection between recent events and anthropogenic emissions provide a illustrative bridge to the future, connecting personal experience of weather with what is to come.

4.1. Attribution of Weather Risk

The occurrence of individual meteorological events cannot themselves be attributed to a specific cause, so all evaluations must examine the risk, or more specifically probability, of such events. The basic framework was laid out in Reference 36, following from the approach used in epidemiology and other fields. Estimates are made of the probability of the event in the current climate and in a hypothetical climate in which anthropogenic activities never influenced the climate system (but external natural forcing still did), as illustrated in **Figure 6**. Crucially, the framework adopts the end-to-end approach to attribution, requiring explicit modeling of the event.

Within this framework, there are a number of possible approaches. Stott et al. (43) examined the risk of the hot summer of 2003 over Europe by conducting a traditional regression analysis on regional summer temperatures to estimate the mean temperature response to various scenarios of historical forcing combinations and then by superimposing an estimate of the internally generated variability of the

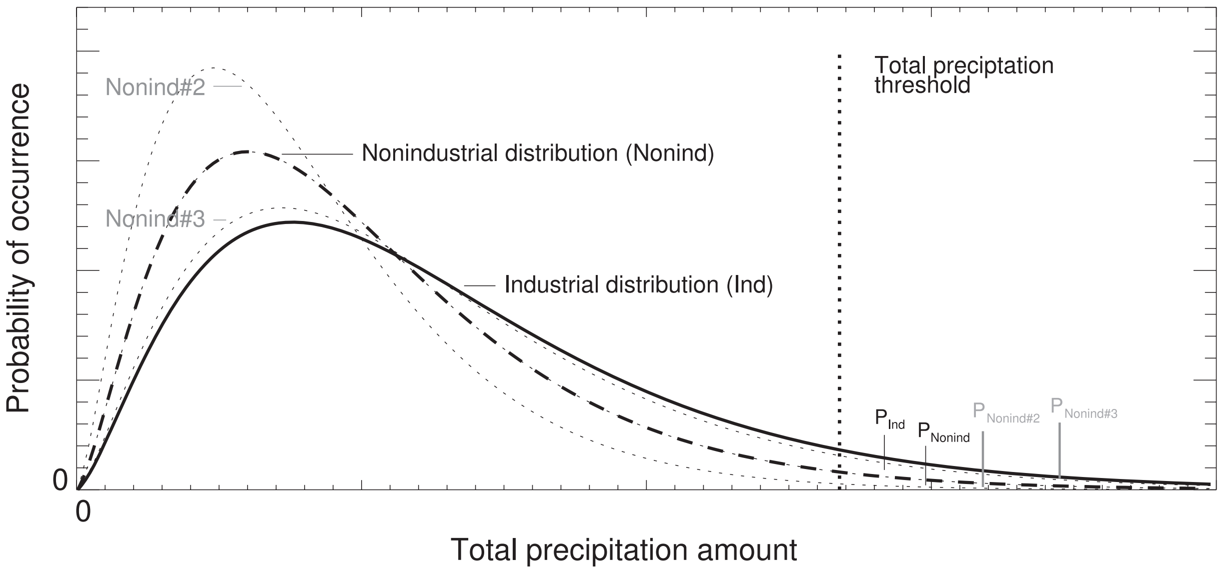

Figure 6

A schematic example of the estimation of the fraction of the risk of occurrence of an extreme precipitation event attributable to anthropogenic emissions. The industrial (Ind) distribution records the probabilities of various precipitation totals in a contemporary climate, and the nonindustrial (Nonind) distribution does so for a hypothetical contemporary climate in which anthropogenic emissions had never occurred. P_{Ind} and P_{Nonind} are the probabilities of an event exceeding a given threshold in the industrial and nonindustrial climates respectively. Following from epidemiological terminology, Stone & Allen (36) describe the fraction attributable risk (FAR) as $1 - \frac{P_{\mathrm{Nonind}}}{P_{\mathrm{Ind}}}$. The values of P_{Ind} and P_{Nonind} are uncertain because of limited data availability. P_{Nonind} is additionally uncertain because it relies on the estimation of the hypothetical climate, with this uncertainty represented in the figure by $P_{\mathrm{Nonind\#2}}$ and $P_{\mathrm{Nonind\#3}}$. Adapted with permission from Reference 42.

climate system, estimated from climate model simulations, onto the estimate of the mean response. The assumptions required appear fine for regional seasonal temperatures but could be questionable for other events. For instance, the variability of precipitation may easily be nonstationary under external forcing (44). Furthermore, accurate representation of synoptic frontal systems, needed for examining precipitation in many regions, requires a climate model to be run at such a high resolution that the traditional regression approach is infeasible.

To get around this, Pall (42) developed an approach that uses a global high-resolution atmospheric model forced with the oceanic response of lower resolution coupled atmosphere-ocean climate models. Using distributed computing (45), estimates of current and hypothetical climates are estimated from thousands of time-slice simulations of this atmospheric model (**Figure 7**), and the two climates are then compared. This is a new approach, so questions remain about specifics. The assumptions involved differ from those in the method of Stott et al. (43). For one thing, estimates of the chance of a severe event are made directly rather than through a statistical model; this may seem more objective, but it may also be more sensitive to the choice of climate model. The main catch is the assumption that the ocean state can be considered external to the climate (i.e., atmospheric) system. This ignores the possibility that feedbacks between the ocean and atmosphere may be important in generating the event. For some events, particularly those occurring in the tropics, these feedbacks are probably quite relevant.

4.2. Current Challenges

Research in this area started only a few years ago, so much remains to be done in developing the approaches. Because studies so far have usually depended on a single climate model, an urgent question is whether the results are robust across different climate models (46). Beyond that, we require a better understanding of the importance of different assumptions that have been used in the various approaches so far. Study of the attribution of the risk of nonmeteorological events, such as floods, also brings all of the issues mentioned in Section 3.

The main challenges at the moment though are not so much technical but rather are the determination of what output is required by potential users and the public at large and then the development a framework that can deliver that output. Outside of the climate change field, most people think of the preindustrial climate as the obvious baseline, but in fact, a nonindustrial climate may be the more relevant, and certainly better posed, see Reference 47. By contrast, some intermediate baseline will be more appropriate in many instances: A water reservoir system should have been designed for the climate of the past few decades, not a distant preindustrial or hypothetical nonindustrial climate. In these cases, the primary interest is in how and why the risk is changing. Additional questions are whether we care about the effects of all external anthropogenic climate forcings, only large-scale forcings, or only greenhouse gas concentrations. Beyond that, is it important to attribute changes in part to internal dynamics of the climate system (40, 48), such as to the phase of the El Niño/Southern Oscillation phenomenon? How can weather risk attribution output feed existing highly developed risk assessment systems? These questions require a dialogue between climate and nonclimate fields that is only in its infancy.

5. FUTURE CHALLENGES IN UNDERSTANDING THE PAST

All of the approaches described in this article have their advantages and disadvantages. Using likelihood measures requires the fewest assumptions but places extremely strong restrictions on how useful models of the climate and nonclimate systems can be. The regression approach places fewer restrictions on the models by using assumptions, which are quite reasonable in some cases, but these assumptions may be less reasonable when examining small spatial scales or nonclimate quantities, which could exhibit highly nonlinear responses. Methods for studying the attribution of weather risk require additional assumptions because observations of the sort of extreme weather risk that interests us are, more or less by definition, very sparse. The end-to-end approach to the attribution of impacts to external climate forcings is logically sound but is also pretty much impossible to implement in most cases. The indirect attribution approaches can be applied in many more cases but use a logic that is at best suspect.

Thus, there is no one-size-fits-all approach. This means that the biggest challenge in the field is the development of a continuum of approaches within an overall framework. Results from indirect attribution analyses will seem much more trustworthy if they are backed with results from end-to-end analyses in analogous situations. Once large ensembles of climate model simulations are produced, it will be possible to compare results using likelihood measures and using regression, which will thus solidify conclusions from the regression studies.

Like climate change research in general, the field of the detection and attribution of climate change has progressed from a narrow research focus to a much broader collection of questions serving multiple needs. The field was initially concerned with only two questions: Is the world warming; are greenhouse gas emissions to blame for that warming (49)? Now questions go beyond warming and beyond even meteorological quantities. Concern is not only about general trends but about trends in the risk of severe events. Sometimes the interest is whether anthropogenic greenhouse gas emissions, or all anthropogenic climate forcings, or all external climate forcings have caused a change. Perhaps the causes are restricted according to date or country. In the case of changes on a nonclimate system, the question may be whether local climate change itself is the cause, irrespective of the ultimate driver of the change in climate.

Once again, a continuum of approaches within an overall framework will be required to deal with these different situations. An increased dialogue with interested parties is also necessary. The difference between a preindustrial and nonindustrial baseline is subtle but is of enormous importance in designing a study and even in determining whether a study is feasible (47). There is also the question of who may be interested in attribution evidence? To date, courts have not accepted evidence from numerical models, but given the nature of the problem, it is hard to see how any reasonable attribution evidence could inform a liability case without using numerical models in some form. Is it possible that courts may alter their policy, and if so, what would be the conditions? Similarly, will the entities making and implementing policy require attribution evidence before instituting measures to adapt to climate change. If so, would circumstantial evidence be sufficiently persuasive? Policy makers are explicitly tasked with making decisions given limited information and may not require the same level of confidence as demanded by a scientific researcher.

The Adaptation Fund, set up under the UNFCCC, is designed to pay for projects that bring about an adaptation to "the adverse effects of climate change" (50). It is as yet unclear whether detection of adverse effects of climate change is a criterion for funding, but in any case, an application would stand a much better chance of success if past effects were demonstrated. Notably though, the UNFCCC defines climate change as attributed to "human activity that alters the composition of the global atmosphere" (1). Thus, adaptation to climate change forced by alterations in land use, for example, is excluded from eligibility for the Adaptation Fund, as is adaptation to naturally forced climate change. Attribution studies would seem to be required then to distinguish between these causes. Certainly, though, attribution studies will be required in the future to evaluate the success of adaptation measures. Many things are required before that can be done, not least of which is the immediate implementation of stable long-term monitoring.

SUMMARY POINTS

1. Research into the detection and attribution of past climate change provides a reference for framing the interpretation of predictions of future climate change.
2. That research also provides unbiased assessments of current weather risk, recent changes in weather risk, and the causes for the changes.
3. The detection of global and continental warming over the past century and the attribution of that warming to anthropogenic greenhouse gas emissions is robust.
4. The detection and attribution of changes in other meteorological quantities appear to be emerging but are not as robust as temperature changes.
5. A number of changes in nonmeteorological quantities have been shown to be consistent with human influence on the climate, but formal attribution of these changes is a challenging problem and the subject of much current research.

FUTURE ISSUES

1. The biggest challenge in the field is the development of a continuum of approaches within an overall framework.
2. A specific issue is if and when extraneous information can be used in detection and attribution analyses, particularly when looking at nonmeteorological quantities.
3. Now that the field is serving multiple purposes, the needs and conditions of those purposes need to be clarified.
4. If attribution analyses are required for the assessment and monitoring of activities designed for adaptation to climate change, then certain measures should be implemented to assist those analyses as soon as possible.

DISCLOSURE STATEMENT

The authors are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

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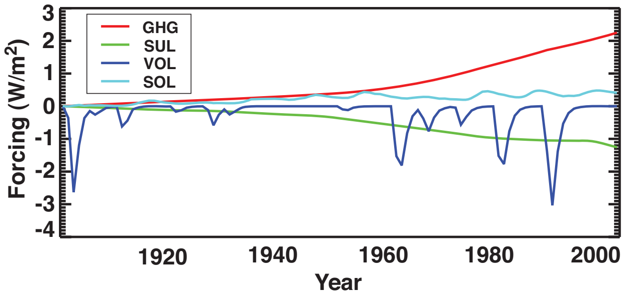


Figure 1

Estimated time series of the influence of various external forcings, measured as the equivalent radiative forcing anomaly at the top of the atmosphere from the 1901 value (8). Abbreviations: GHG, forcing from anthropogenic greenhouse gas emissions; SUL, forcing from anthropogenic sulfate aerosols; VOL, forcing from natural stratospheric volcanic aerosols; SOL, forcing from natural changes in the solar luminosity; W/m^2, watts per horizontal square meter.

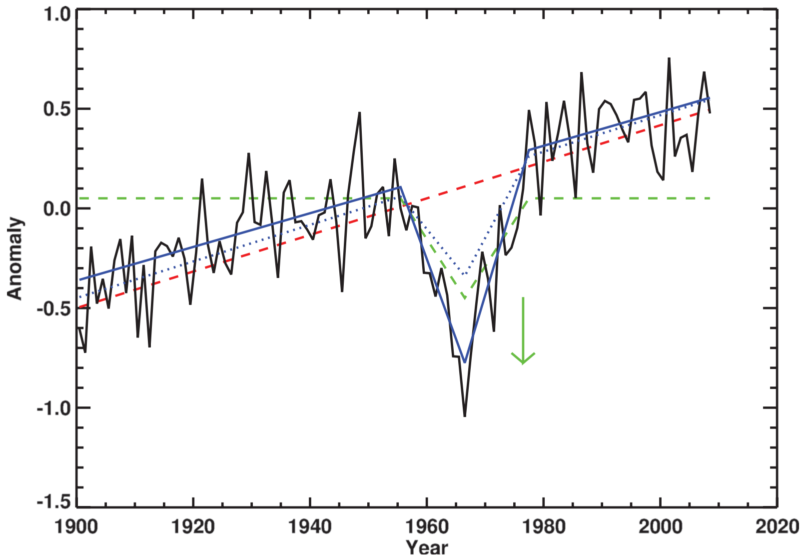
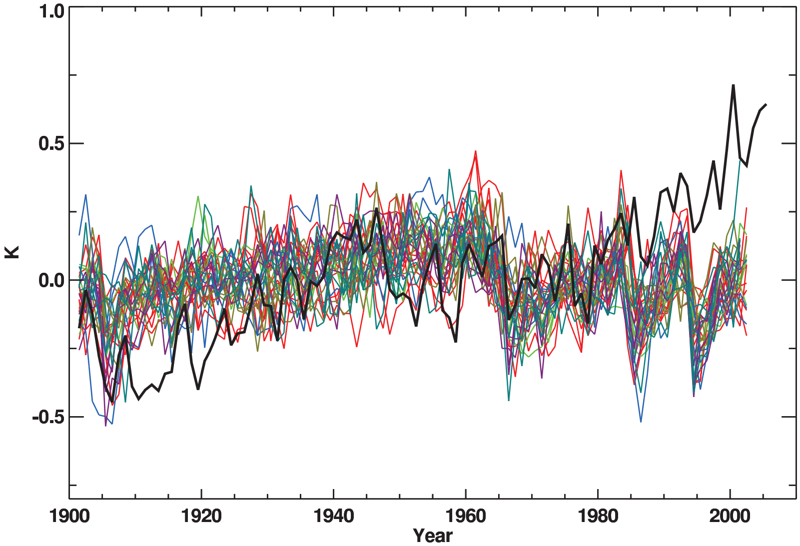


Figure 2

A schematic of how the standard regression method works. The black line shows an observed time series of some meteorological variable in arbitrary units. The dashed red and green lines show the responses of a climate model to variations in two separate external forcings. The dotted blue line is the combined climate model response to both forcings. A multiple regression analysis reveals that both responses are detected in the observed time series but that the green response must be amplified by a factor of two in order to fit properly. The adjusted combined climate model response, with the green response amplified by a factor of two, is shown as the solid blue line.



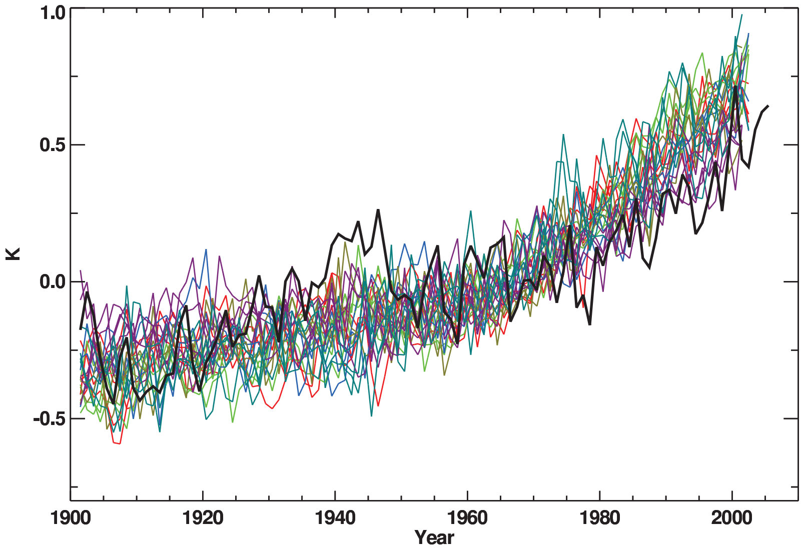


Figure 3

Comparisons of observed annual global mean surface temperature against results from climate model simulations under various historial forcing scenarios. (*top*) When the climate models are forced with changes in only natural external forcings. (*bottom*) When the climate models are forced with changes in only greenhouse gas concentrations. (*next page*) When the climate models are forced with changes in all expected major forcings. In each panel, the observed time series is in black. Other colors denote simulations of a specific climate model, with multiple simulations differing in the initial states. Values are anomalies from the 1901–1999 average. Results from six climate models are shown here in different colors. Note how the model results differ in some aspects, with for instance the red and light green models expecting cooler recent decades than the other models in response to all expected major forcings (*bottom*). Abbreviation: K, Kelvin.

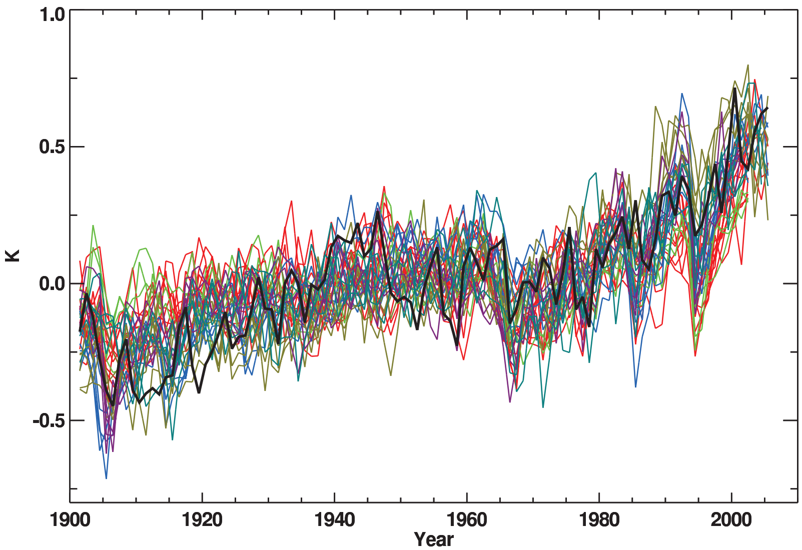


Figure 3

(*Continued*)

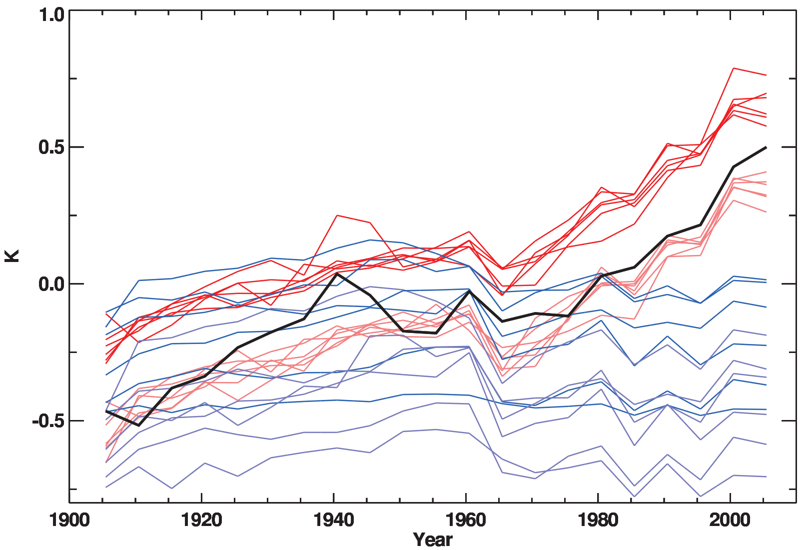


Figure 4

Similar to the first and last panels of **Figure 3** but with climate model output adjusted according to regression against the observations. The observed variations are shown in black. Light and dark pairs of blue lines show the approximate 5% to 95% range of what would have been expected for the historical record if the climate had only been influenced by natural forcings, whereas the light and dark pairs of red lines show the approximate 5% to 95% range of what would have been expected under the influence of all known forcings. Each pair of lines corresponds to one of the six climate models. Note how all models now agree more closely in their estimated responses to all known major forcings (versus the last panel of **Figure 3**). The expected responses to natural forcings have also been adjusted vertically to show how a natural climate would differ from the climate we have actually experienced; the spread in estimates of the natural response is large because of uncertainty in the size of this vertical adjustment. Abbreviation: K, Kelvin.

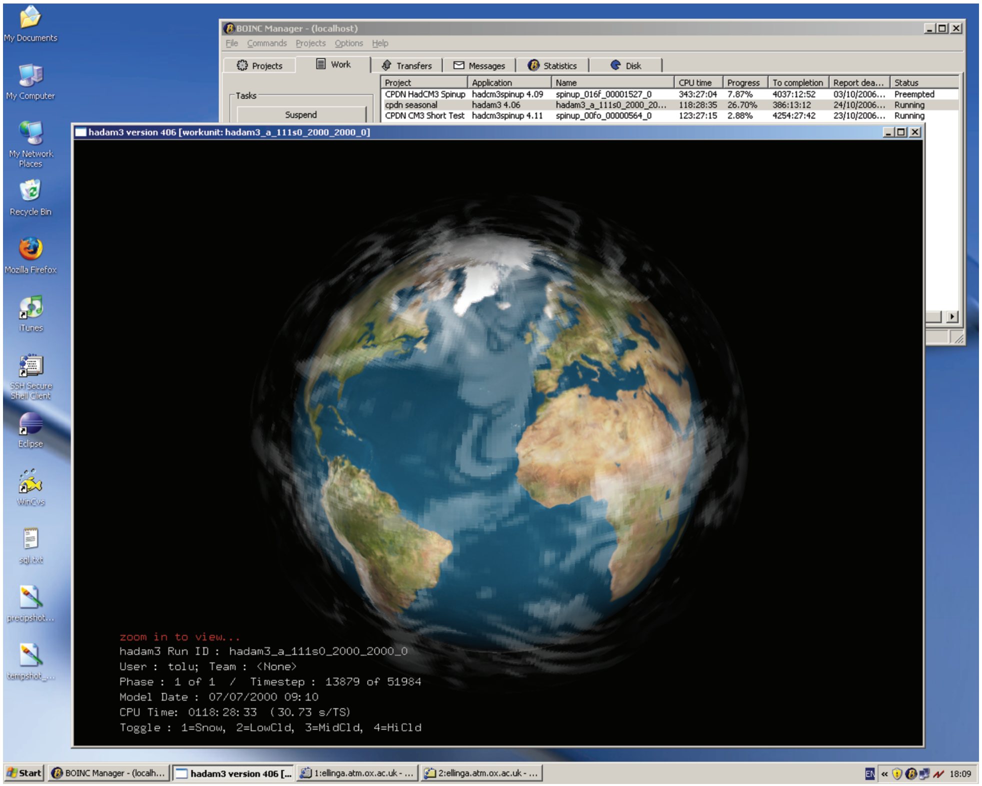


Figure 7

A screenshot of a typical weather simulation running on a volunteered home personal computer under a Windows™ operating system. Note the realistic patterns of cloud formation produced using this high-resolution global atmospheric model. Reproduced with permission from Reference 42.

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