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Quantifying the Human and Natural Contributions to Observed Climate Change

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20.1 Introduction

The natural climate is characterized by enormous amounts of chaotic variability that we experience as weather on short time scales and as year-to-year (and longer) differences in climate characteristics. Not only do we experience variations in temperature, precipitation, wind speed and so on within the course of a few days, but we also experience a summer, for example, that may be warm or cool, dry or wet, or be otherwise distinguished from other summers. This natural chaotic variability is driven by the energy from the Sun, which is absorbed by the Earth and re-emitted to space in the form of heat. Much of the weather and climate variability we experience results from the transfer of energy from places where it is absorbed to places where it is ultimately radiated back to space. This variability occurs spontaneously, and would occur even in the absence of any external influences on the climate, such as that from volcanic eruptions. Thus climate scientists often refer to this variability as natural internal climate variability.

In the absence of external influences on the climate, the amount of incoming solar energy is balanced by an equal amount of outgoing heat. External influences which affect that balance are called *forcing* agents. One group of forcing agents that has been recognized since the time of Joseph Fourier (Fourier, 1824) is greenhouse gases such as carbon dioxide. Increasing the greenhouse gas concentration in the atmosphere makes it less transparent to the passage of the infrared radiation (heat) that is trying to escape to space, which implies that the climate should become warmer. The atmospheric concentration of carbon dioxide has increased markedly since the beginning of the industrial revolution, increasing from about 280 ppm in 1750 to about 400 ppm today. This rise is principally from fossil fuel use and changes in land use, such as deforestation. Concentrations of other important greenhouse gases, such as nitrous oxide and methane, have also increased. Other external influences that affect the Earth's energy balance include changes in the Earth's orbit around the Sun, changes in the Sun's energy output, volcanic eruptions that affect the amount of reflective aerosol present in the stratosphere (which reduces the amount of solar energy that reaches the Earth's surface), human induced changes in atmospheric aerosol concentrations and changes in land surface properties related to development activities (e.g., due to urbanization and conversion to agricultural uses).

The climate that we experience can be thought of as a combination of the effects of a suite of external forcing agents, including human induced greenhouse gas increases, and natural internal climate variability. Invariably, a conceptual or physical model of some kind is used to estimate the expected effects of those forcing agents. Subsequently, a range of statistical techniques is used to attempt to detect these estimated signals in climate observations, and ultimately, to attribute causes to observed changes.

20.2 Scope of the Problem

Before beginning, it is worth considering some of the details of the climate observations in which we might look for evidence of the effects of increasing greenhouse gases or other external forcing factors. For example, the global mean surface temperature has warmed by approximately .7°C over the period 1901–2010, and we might want to determine whether external influences on the climate played a role in that warming. To do so convincingly, it will be necessary to consider not just the trend in global mean temperature, but also the evolution of the spatial pattern of warming over time, to be sure that the observed change was not of natural origin.

The warming pattern that is expected from human influence on the climate is distinct from natural patterns of internally caused surface temperature variability. Based on physical considerations we expect that the forcing from human influences on the climate should lead to more warming over land than over oceans and more warming at high northern latitudes than elsewhere due to feedback processes operating in the Arctic that help to amplify the climate response to human influences. We also expect that warming will evolve somewhat differently in different places because some forcing agents, such as aerosols, have regional as well as global scale effects. Thus the pattern of expected change is complex, with spatial features that evolve slowly over time.

Many studies therefore consider only decade-to-decade changes in surface temperature. For example, Jones et al. (2013) considered the evolution of decadal mean surface temperature patterns of the 11-decade period 1901–2010. The decadal surface temperature patterns are often based on decadal mean temperatures in regions of approximately 250,000 km^2 (areas about the size of United Kingdom that span 5° of latitude and longitude). If it were possible to calculate a decadal surface temperature average for every such region on the face of the Earth for every decade in the 11-decade period, there would be a total of 28,512 decadal means (11 decades $\times$ 2592 regions). Even considering that in many regions decadal averages cannot be calculated because insufficient observations are available to estimate a regional mean for that decade, there are nevertheless thousands of decadal values. Thus the observed space-time pattern of surface temperature changes has very high dimension when organized as a space-time data vector. Since the expected pattern of change is spatially smooth, most studies reduce the spatial dimension of the problem by retaining the equivalent of about 25 subcontinental regional means to represent the large-scale surface temperature pattern for each decade, which still implies an observed space-time data vector of length 275.

Thus the sheer size of the problem poses a challenge. While the observed pattern of change is simplified substantially by considering only decadal means over very large areas, we are still faced with the fact that the presence or absence of a human signal in this very large scale pattern of observed change needs to be assessed relative to a background of considerable natural internal climate variability. However, it is not possible to estimate the characteristics of the natural internal climate variability directly from observations since the historical observations are presumably affected by external forcing. Moreover, the pattern of change that we are interested in involves most of the available historical instrumental surface temperature observations; temperature readings from thermometers become increasingly sparse as you go back into the 19th century, with readings available in the 18th century in only a few isolated locations. The approaches that have been developed in statistical science for modeling the behavior of high dimensional space-time processes are generally not used (Cressie and Wikle, 2011) because most involve assumptions about the properties of the natural internal variability that are not well justified (e.g., assumptions such as isotropy in space, which can hardly be expected given the land-sea distribution of the Earth). Approaches that take advantage of some of the expected properties of the covariance matrix, which describes how variations at different times and places are related (Rajaratnam et al., 2008; Guillot et al., 2013) are also only rarely used at the moment, although there are exceptions, such as Ribes and Terray (2013).

Instead, estimates of the covariance matrix of the background internal climate variability are usually based on climate simulations obtained from climate models that have been run under control conditions (i.e., with constant atmospheric composition, no episodic volcanic influences, and no variation in solar output). In some cases, it has been possible to use climate models to simulate several thousand years of the evolution of the climate under such conditions, thus providing up to 100, or possibly more, simulated realizations of how the climate might have evolved in the absence of external influences since 1901. These 100 or so pseudo-realizations of the unperturbed climate are used to calculate a sample covariance matrix that estimates the true covariance matrix of the internal variability.

20.3 A Weighted Regression Approach

A general approach in detection and attribution studies is to regard an observed climate change Y as a linear combination of externally forced signals X and residual internal climate variability ϵ (Hegerl and Zwiers, 2011), viz.

$$Y = X\beta + \epsilon, \tag{20.1}$$

where vector Y is a filtered version of the observed record, the columns of matrix X contain estimates of the effects of the external forcings that are under investigation, and β is a vector of regression coefficients that adjust the amplitudes of those expected patterns of change so that the linear combination matches the observations as closely as possible.

Typically, X contains no more than three columns (e.g., representing the responses to greenhouse gas changes, the combined effects of other anthropogenic influences such as aerosol emissions and land surface changes, and the combined effects of natural external influences from explosive volcanic eruptions and changes in solar output). Each column in X is estimated from a set of climate model simulations in which the climate model has been run with the forcing that corresponds to that column. For example, the first column in X might contain estimates of expected surface temperature changes that are derived from climate model simulations run with the observed history of greenhouse gas concentration changes, the second column might be based on additional runs using the observed history of aerosols and land surface changes, and perhaps a third might be based on runs with the observed history of volcanic eruptions and changes in solar output.

In Figure 20.1, for example, which is based on the assessment of Hegerl et al. (2007), we suppose that the observed 1901–2005 change in surface temperature (Figure 20.1(a), representing the vector Y) can be represented as a combination of the effects of two kinds of forcing, which are represented by Figures 20.1(b) and 20.1(c). Figure 20.1(b) shows an estimate of the effects of human induced forcing (greenhouse gases, aerosols, land use effects, etc.) and natural external forcing (solar output changes and volcanic forcing) combined, and could be considered as a candidate for the first column of matrix X, say X_1. Figure 20.1(c) shows an estimate of the effects of natural external forcing only, and could be considered as a candidate for the second column of

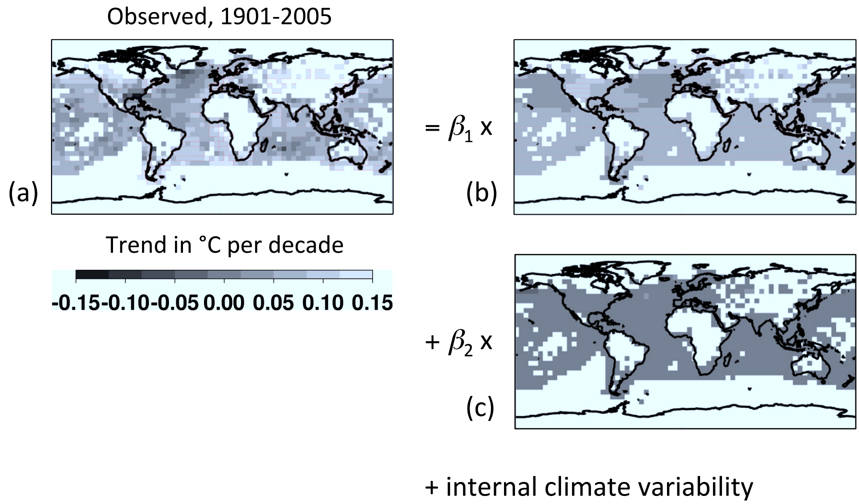

FIGURE 20.1: After Hegerl and Zwiers (2011), based on Hegerl et al. (2007): Schematic for detection and attribution. The observed change (panel (a), shown here as the pattern of temperature change over the twentieth century) is assumed to be composed of a linear combination of the effects of two kinds of external forcing plus the effect of internal climate variability. Panel (b) shows an estimate from climate models of the effects of all forcings combined, which includes human induced forcings and natural external forcings. Panel (c) shows an estimate from climate models of the effects of natural forcings only. See text for further details. Units are °C.

the matrix, say X_2. The amplitudes of the two patterns of forced change are adjusted with the coefficients β_1 and β_2 that make up the vector of regression coefficients β so that the sum best matches the observed changes. Note that in climate science, these regression coefficients are also often referred to as scaling factors.

It is assumed that the effects of human induced forcings and natural forcings add linearly. Thus the figure supposes, as does Equation (20.1), that

$$Y = \beta_1 X_1 + \beta_2 X_2 + \epsilon,$$

where

$$X_1 = X_{\mathrm{ANT}} + X_{\mathrm{NAT}}, \quad X_2 = X_{\mathrm{NAT}},$$

with X_{ANT} and X_{NAT} representing the effects of human induced (ANThropogenic) and NATural external forcings respectively. Equivalently, this also means that $Y = \beta_1 X_{\mathrm{ANT}} + \beta_2^{'} X_{\mathrm{NAT}} + \epsilon$, where $\beta_2^{'} = \beta_1 + \beta_2$. This small algebraic manipulation is required because climate modeling centers have most frequently produced separate ensembles of simulations with the anthropogenic and natural forcings combined and with natural forcing only, in preference to separate ensembles of simulations with anthropogenic forcings only and natural forcings only.

Depending upon the study, vector Y and the columns of X may be of dimension of 275 or so, representing the decade-by-decade evolution of the large-scale spatial pattern of changes in a climate variable such as surface temperature over the 110-year period from 1901 to 2010, where each decadal spatial pattern has about 25 spatial components in each decade; see, e.g., Jones et al. (2013). It should be noted that the climate model output is spatially and temporally complete (there are no missing values), whereas the observations are often missing, both in space and in time. Figure 20.1(a) shows linear trends in surface temperature over the period 1901–2005. Trends are shown for $5° \times 5°$ latitude by longitude regions that are judged to have sufficient observations to allow the reliable estimation of trends. Grey areas in Figure 20.1(a) indicate locations where trends cannot be estimated due to insufficient data being available. This includes some large parts of the global oceans where historically, there was little ship traffic (up until recently, most ocean surface temperature readings were collected by commercial ships). Also, there are data voids in both polar regions and over several large land areas (particularly in South America, Africa, and parts of Asia) either due to an insufficient observing network, because archived paper records have not yet been digitized, or, in some cases, because national meteorological services do not have the mandate or resources to disseminate the data that they gather. As shown in Figures 20.1(b)–(c), the climate model output is therefore made to be missing at the same times and places as the observed data so that a like with like comparison can be made between the observations and the models.

The scaling factors (regression coefficients) β are often estimated by the so-called weighted least squares method as

$$\hat{\beta} = (X^\top C^{-1} X)^{-1} X^\top C^{-1} Y = (\tilde{X}^\top \tilde{X})^{-1} \tilde{X}^\top \tilde{Y}.$$

Here the matrix $\tilde{X}$ and vector $\tilde{Y}$ are the weighted versions of the signal patterns and observations, such that after weighting, the estimator of the regression coefficients looks like that used in the ordinary least squares method. This weighting reduces the uncertainty of the scaling factors $\hat{\beta}$ (Hasselmann, 1997; Allen and Tett, 1999), although in some detection and attribution problems, that benefit is difficult to realize because of difficulty in determining a complete set of weights; see, e.g., Hegerl et al. (1996) and Polson et al. (2013). The weighting is based on an estimate of the covariance matrix of the climate's natural internal variability, which as explained above, is derived from a limited set of climate model control runs. Thus the weights themselves are uncertain. Climate scientists account for that uncertainty by using a second set of climate model control simulations to estimate the natural internal variability of $\tilde{Y}$ (Hegerl et al., 1997; Allen and Stott, 2003) and consequently, the uncertainty of the regression coefficients $\hat{\beta}$.

Having fitted regression model Equation (20.1) to the observations, climate scientists ask essentially three questions.

1. Is the residual variability $\hat{\epsilon} = Y - X\hat{\beta}$ consistent with the estimates of natural internal climate variability obtained from climate model control simulations? If not, then the rest of the analysis is drawn into question since the criteria that will be used to evaluate questions about the regression coefficients depend on estimates of internal variability from climate models. One approach that has been used in such cases is to proceed to questions (ii) and (iii) after arbitrarily inflating the climate model simulated variability by a factor of 2 or more.
2. Are the estimated regression coefficients $\hat{\beta}$ significantly greater than zero? If not, then there is insufficient evidence to support the idea that observations reflect the estimated effects of external forcing that are described in matrix X.
3. If there is evidence that the expected effects of external forcing are reflected in the observations, then does their magnitude correspond to that which is expected based on our theoretical understanding of the physical processes that link forcing to its effects and given known uncertainties, for example, in the magnitude of forcing and its influence on climate?

We will come back to these inference questions in Section 20.6, but before doing so, it is important to describe the role of the climate models in detection and attribution studies in a bit more detail.

20.4 Role of the Global Climate Models

Most recent detection and attribution work uses signal patterns, often called fingerprints, that vary in time, space, or both. In the case of space and time, you can think of the fingerprints as a time series of patterns of changes that are expected at different times from a given forcing (or set of forcings combined). Figures 20.1(b)–(c) illustrate two spatial fingerprints (expected patterns of change over a 105-year period), but you could also easily imagine a time series of patterns connected together, describing the expected change decade-by-decade.

The fingerprints are almost always obtained from comprehensive climate models, consisting of coupled atmospheric and oceanic models that simulate winds and currents and are based on the principles of thermo- and fluid-dynamics, together with sea ice, land surface, and ice-sheet models, and often also, interactive vegetation, carbon cycle and chemistry components. While the physical and chemical processes represented by these models can be described mathematically in a relative concise manner, the equations that comprise the models are far too complex to be solved mathematically. Hence, the equations are "discretized" and solved via large-scale computer calculations (runs) using some of the largest computers on the planet. By discretized we mean that the equations are approximated in such a way that the atmosphere and ocean are represented by sets of cubes covering the Earth and extending upward through the atmosphere and downward through the depths of the ocean, the land surface is represented by a set of tiles that covers the Earth (or several layers of tiles to represent how soil properties vary with depth), and time passes by in fixed increments (time steps).

Typically, such models will have a spatial resolution of about two degrees latitudinally and longitudinally (Kharin et al., 2013) with time steps of 15 minutes or so, although higher resolution models are increasingly being developed. For example, global weather forecasting models, which are closely related to climate models, often have resolutions of about 35 km and there are examples of global climate models with 20 km resolutions.

Comprehensive global climate models (GCMs) simulate the natural internal variability of the climate as well as the response to whatever external forcing may be specified when the model is run. For example, when these models are run with the historical evolution in greenhouse gas concentrations, aerosols, land use change, volcanic eruptions, and changes in solar output since the beginning of the industrial revolution, they simulate changes in global mean temperature similar to those that have been observed; see, e.g., Hegerl et al. (2007) and Jones et al. (2013). The warming response to these forcings is very evident in the global mean because spatial averaging removes a substantial part of the simulated internal variability, but the spatial pattern of warming and how it evolves over time is considerably noisier.

Many detection and attribution studies estimate the response to external forcing by averaging across an ensemble of GCM runs (independent realizations that are obtained by starting the model from slightly different initial conditions each time) to reduce the effects of internal variability on the signal estimates. The signal estimates are also subject to other sources of uncertainty including errors in the formulation of climate models or the omission of some processes that may be climatically important (such as the nitrogen cycle, which is thought to have an important role in mediating the carbon cycle but is not currently represented in all models containing carbon cycle components), forcing uncertainty, possibly missing forcings that are not included in the simulations, and parameter uncertainty (climate models must necessarily parameterize, or approximate, processes that they cannot resolve, and the adjustable parameters in those approximations are often uncertain). Parameter uncertainty in the representation of processes involving clouds and aerosols, in particular, remains large, and one of the implications of this is that the effects of aerosols on the lifetimes and reflectivity of clouds continues to be a very large source of uncertainty in simulating historical and future climate changes. This in turn affects our understanding of a much discussed climate system parameter, the so-called equilibrium climate sensitivity, which is an indicator of the amount of warming that we might eventually experience if carbon dioxide concentrations were to double relative to pre-industrial levels, and remain at that level.

The costs of operating the models are such that it is rarely possible to simulate, with a given model, more than about ten realizations of the evolution of the climate since the end of the pre-industrial era (around 1850) to the present; most modeling centers, in fact, produce smaller ensembles, with five or fewer simulations. Thus estimates of the effects of forcing from individual models are necessarily affected by sampling variability and other important sources of uncertainty as mentioned above.

20.5 A Slightly More Detailed Regression Model

The regression model of Equation (20.1) is often replaced with a slightly more complex errors-in-variables (EIV) model to account for uncertainties in the estimated effects of forcing. This model is fitted with the so-called total least squares algorithm (Allen and Stott, 2003) and has the form

$$Y = (X - \delta)\beta + \epsilon, \tag{20.2}$$

where the columns of random matrix δ are independent of ϵ but have covariance matrices that are proportional to that of ϵ. The term δ is introduced in this model to account for the fact that the signal estimates that make up the columns of X are subject to sampling uncertainty since they are estimated from finite ensembles of climate change simulations. For example, if the signals are estimated using an ensemble of five independent historical climate change simulations from a given climate model, then the columns of δ will have covariance matrices $C_{\delta\delta} = C/5$, where C is the covariance matrix of ϵ that represents the effects of internal variability in the observations Y.

More generally, the signals are estimated by averaging signal estimates from multiple climate models, substantially reducing uncertainty from internal variability in X, but introducing uncertainty due to inter-model differences. Typically this is treated using Equation (20.2), although on rare occasions, studies have used a more complex errors-in-variables model modified to recognize explicitly that X is affected by two sources of sampling variability — from the selection of climate models (discussed below) and from internal climate variability (Huntingford et al., 2006). Philosophically, however, this is difficult since we have no clear way to describe how the "sample" of available models was drawn from the population of conceptually plausible representations of the climate system; see, e.g., Rougier et al. (2010) and von Storch and Zwiers (2013). Also, many current climate models are developed, in part, by using components that are developed elsewhere since no one modeling center has the expertise or capacity that would be required to develop a complete model independently. Thus there is a question of the extent to which simulations from different models are "independent"; see, e.g., Jun et al. (2008). Here the notion of independence again refers to how the population of all plausible climate models is being sampled by the climate modeling community.

The selection of climate models for a given purpose remains a difficult question. Current international climate modeling activities are largely coordinated through the *Coupled Model Inter-comparison Project, Phase 5* or CMIP5 (Taylor et al., 2012), which sets out a number of standard protocols for running climate change simulations in order to facilitate their intercomparison. At last count, about 25 modeling centers around the globe with a combined total of about 60 different model variants were CMIP5 participants; see `http://cmip-pcmdi.llnl.gov/cmip5/availability.htmlforCMIP5statusupdates`. It is well recognized that not all models are of equal quality, but objective measures of model quality are very much dependent upon the climate variable of interest, and overall measures of quality remain somewhat subjective (Gleckler et al., 2008); see the discussion of Knutti et al. (2010).

A very frequently encountered problem in fitting the models (20.1)–(20.2) is that the sample covariance matrices $\hat{C}$ are not of full rank despite filtering that retains only decadal scale temporal variability and continental, or larger scale, spatial variability. Rank refers to a property of matrices such that a matrix has full rank if no column in the matrix can be expressed as a linear combination of its remaining columns; the standard scheme for finding weights for fitting models (20.1) or (20.2) depends upon $\hat{C}$ having full rank.

For example, the space-time surface data vector used by Jones et al. (2013) has dimension 275, but it remains difficult to produce full rank estimates of a covariance matrix with 275 rows and columns from currently available climate simulations. This is because, despite the availability of ever more extensive coordinated international climate model intercomparison exercises such as CMIP5, the total number of century-long control simulation segments that have been run by the different modeling centers remains limited. The implication is that unique weights based on $\hat{C}$, as described in Section 20.3, for fitting regression models (20.1)–(20.2) cannot be obtained; thus regularization, in which constraints are placed on $\hat{C}$, has been proposed.

Most studies use a regularization approach that is based on decomposing $\hat{C}$ according to its so-called eigenvectors, which are called Empirical Orthogonal Functions or EOFs in climate research (von Storch and Zwiers, 1999). The observations and signals can be expressed uniquely as linear combinations of these EOFs (i.e., as a sum of EOFs multiplied by uniquely determined weights). The EOFs are ordered according to their ability to represent the variability that is present in the observations, and generally, a large fraction of the total variability can be represented with only a small number of EOFs. Regularization is thus performed by approximating the observations and the signals using a number of EOFs that is substantially smaller than the length of the data vector Y. In the surface temperature problem, this effectively replaces a data vector Y that is of length 275 with one that is much shorter — typically with 30–40 elements (Jones et al., 2013) — thus making it feasible to calculate a full rank covariance matrix with the available collection of control runs. The columns of the signal matrix X are similarly shortened.

Recently, Ribes et al. (2009, 2013) have proposed an alternative regularization approach which attacks the problem by estimating the covariance matrix differently, using the method of Ledoit and Wolf (2004), which modifies the sample covariance matrix so that it has full rank. This implies that an EOF approximation is not required for either the observations Y or the signals X. While the formalism of Ribes et al. is only beginning to be used in detection and attribution research Ribes and Terray (2013), it has the advantage that all data reduction decisions (such as the decision to use decadal mean temperatures averaged over very large regions) that are taken to reduce dimensionality or increase signal-to-noise ratios are performed prior to fitting any regression model. In contrast, this occurs in two stages in most current detection and attribution studies, with data reduction taking place prior to the analysis and typically also within the analysis as a consequence of the EOF-based approximation of the observations and the signals.

20.6 Interpreting the Results

Regression models such as (20.1) or (20.2) are used in detection and attribution studies to support the interpretation of observed climate changes, such as the warming that has taken place since the beginning of the twentieth century. As explained at the end of Section 20.3, this involves three kinds of statistical inferences.

First, the fit of the regression model to observations is assessed by means of a residual consistency test, which compares the estimated residual variability in $\hat{\epsilon} = Y - X\hat{\beta}$ or $\hat{\epsilon} = Y - (X - \hat{\delta})\hat{\beta}$ with an estimate of internal climate variability. In both cases, the test statistic can be evaluated with the familiar Fisher–Snedecor F distribution. Unexpectedly small or large values of this statistic would flag that the climate model (or models) that have been used to estimate the covariance of the internal variability do not, in fact, simulate that variability correctly. Also, unexpectedly large values of the statistic might indicate that the climate model simulated signals have a different form from those that are actually reflected in the observations. For example, the discrepancy between a climate model simulated response to human induced forcing and observations would be larger than could be explained by internal variability if the climate model simulated the same amount of warming over land as observed, but less warming than observed over oceans. In the case of surface temperature, the available evidence suggests that climate models do simulate internal variability reasonably well on the space and time scales that are of interest in detection and attribution studies; see, e.g., Hegerl et al. (2007) or Jones et al. (2013).

Once we are satisfied that the statistical model fits the observations reasonably well, the next step is to determine whether the climate changes that are expected from external forcing are reflected in the observations. This is accomplished by testing the hypothesis that the regression coefficients (or scaling factors) β are greater than zero. If, for example, global surface temperature observations reflect the warming effect of human influences on the climate system, then the regression coefficient that modifies the amplitude of the climate model's simulated warming effect of that influence should be significantly greater than zero. In contrast, if the scaling factor is indistinguishable from zero, or substantially negative, then we do not have evidence that the corresponding signal is present in the observations.

In Figure 20.1, it is evident that the observed pattern of surface temperature change, in this case for the period 1901–2005 — see Figure 20.1(a) — has a strong resemblance to the pattern of warming that is expected from the combination of human and natural external influences on the climate (Figure 20.1b) and little or no resemblance to the pattern of surface temperature change that is expected from natural external influences (i.e volcanic and solar forcing forcing) alone — see Figure 20.1(c). Numerous studies indicate that the scaling factor β_1 that multiplies the expected pattern of change due to human influence on the climate system is significantly greater than 0 at a very high significance level, while the scaling factor β_2 that multiplies the expected pattern of change due to volcanic and solar forcing is indistinguishable from zero. This then leads to the conclusion that human influence on the climate is clearly detectable; see, e.g., Hegerl et al. (2007).

Assuming that the expected patterns of change are detected (i.e., one or more of the scaling factors is found to be significantly larger than zero, indicating that the corresponding signal is likely reflected in the observations with non-negligible amplitude), then a further question is whether the climate model simulated amplitude of the expected signal corresponds to its amplitude in observations. Our physical understanding of the climate system, which is embodied in the climate models, plus our understanding of the forcing, leads to a physically based estimate of the response to external forcing that is expressed in physical units; see, e.g., °C in Figure 20.1(b). In the case of surface temperature, this is illustrated by Figure 20.1(b). If, for example, we have underestimated the forcing, the climate models would still be expected to produce the same pattern of expected surface temperature change, but it would be more muted than if the forcing had been specified correctly. This in turn would lead to estimates of regression coefficients with values that would tend to be greater than one, indicating a need to scale up the climate model simulated signals, and thus compensating for the error in forcing. Similarly, regression coefficients that are different from one would compensate for a climate model that responds either too vigorously (estimated regression coefficient less than 1), or not vigorously enough (regression coefficient greater than 1) because its sensitivity is not correct; see Section 20.4. Thus the question of the consistency between the signal amplitude simulated by a climate model, and the amplitude of that signal that is reflected in the observations, is an important one. The consistency can be evaluated by examining confidence intervals for the estimated scaling factors, and determining whether those intervals include "1."

Detection and attribution research on the evolution of surface temperature during the twentieth century was assessed for the 4th Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) by Hegerl et al. (2007). They evaluated studies using individual and multiple climate models combined that considered whether three externally forced signals (the effects of greenhouse gas increases, other human influences, and natural external influences) were reflected in twentieth century observations. Figure 20.2(a) shows the regression coefficients that are obtained when signal estimates produced with different climate models or a group of climate models combined are used to evaluate observed large-scale changes in surface temperature over the 10-decade period 1901–99. These analyses cover only the period up to 1999 because the historical climate model simulations available at the time did not extend beyond 1999. The figure shows central estimates of the scaling factors and 90% uncertainty bands. Regardless of the climate model used, the signals associated with greenhouse gas increases (light gray intervals) and other anthropogenic influences (dominantly aerosols, medium gray intervals) are clearly detected. Also, scaling factor estimates are generally consistent with 1, although there is a small tendency for the climate models to warm slightly more due to greenhouse gas forcing than is supported by the observations. The response to natural external forcing (solar and volcanic activity, dark gray intervals), is also detected based on some models and in the multi-model "EIV" analysis, but less consistently. Recall, however, that this signal is weak; see, e.g., Figure 20.1(c).

Having detected the presence of an externally forced signal in observations, and after evaluating whether its amplitude in observations is consistent with the amplitude that is expected from climate model simulations, a further step is to attribute part of the observed change to external forcing. As we have seen, in the case of surface temperature, the patterns of change that are theoretically expected to result from human induced emissions of greenhouse gases and aerosols are found in observations and have about the right amplitude. Other explanations, such as the possible effects of changes in volcanic activity and solar output, do not provide a plausible explanation (e.g., compare Figures 20.1(a) and 20.1(c)), and the pattern of change that is seen is not one that could easily be explained by natural internal climate variations. Thus we must conclude that human induced changes are likely responsible for most of the observed change over the latter half of the twentieth century on all continents except Antarctica (Hegerl et al., 2007).

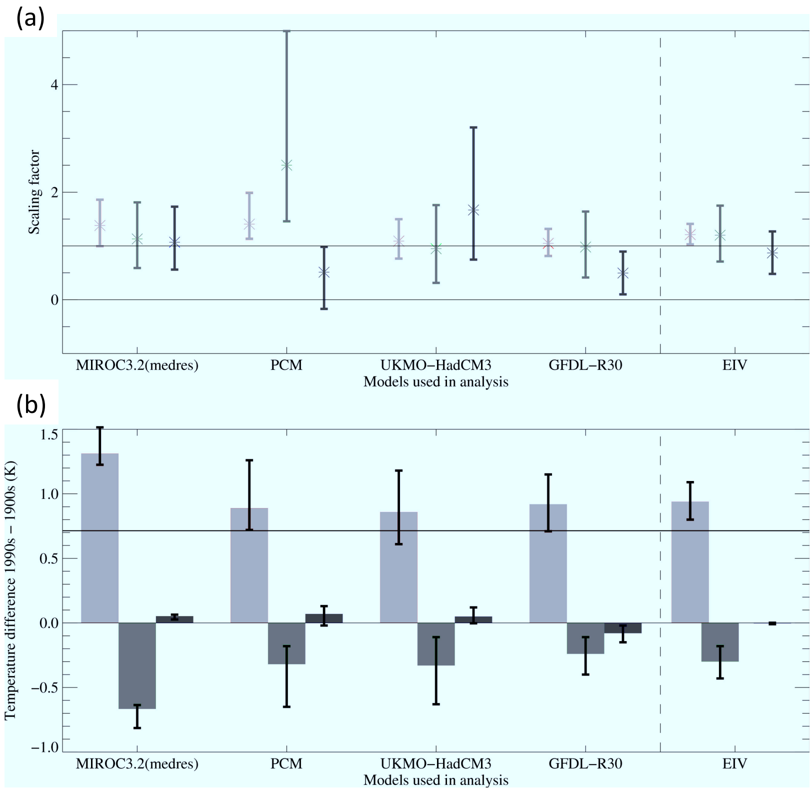

FIGURE 20.2: From Hegerl et al. (2007): (a) 5 to 95% uncertainty limits on scaling factors (dimensionless) based on an analysis over the twentieth century, and (b) the estimated contribution of forced changes to temperature changes over the twentieth century, expressed as the difference between the 1990 to 1999 mean temperature and the 1900 to 1909 mean temperature (°C). The horizontal black line in (b) shows an estimate of the observed temperature change. Detection and attribution results were obtained using estimated responses to external forcing from four different climate models (labeled MIROC3.2(medres), PCM, UKMO–HadCM3 and GFDL–R30) in separate total least squares analyses (i.e., using Equation (20.2)). Also shown, labeled "EIV" are the results of an analysis simultaneously using estimated responses from three models (PCM, UKMO–HadCM3 and GFDL–R30) that explicitly considers inter-model uncertainty. See Hegerl et al. (2007) for details and sources for individual results.

An interval estimate of the size of the detected and attributed effect in observations over the twentieth century can be obtained by multiplying the climate model estimates of the effects (from the columns of matrix X) with the confidence range of the estimated scaling factors. This is shown in Figure

20.2(b), which shows a set of estimates of attributed warming or cooling (bars) with an estimated uncertainty (whiskers) for each of three external forcing agents and several different analyses using either individual climate models or an ensemble of climate models. The bars are obtained by scaling the climate model simulated change in global mean temperature between the first and last decades of the twentieth century by best estimates of the scaling factors for the responses to the forcings represented by the bars.

The estimated uncertainty in the attributed warming or cooling reflects the uncertainty in the corresponding scaling factor, but not other sources of uncertainty such as forcing uncertainty. The figure shows that greenhouse gas forcing, acting on its own, would likely have warmed the planet substantially more than observed during the twentieth century and that this was partially offset by the cooling effects of other anthropogenic influences. It should be noted that, even if a model's sensitivity to greenhouse gas changes was overestimated, or its sensitivity to aerosols underestimated, the estimated scaling factor would correct for this by scaling the model simulated response to best match the observed changes. Of course, substantially more is required for definitive attribution assessment than simply an evaluation of signal scaling factors; also required is a set of strong physical arguments that would rule out other factors as a plausible explanation of the observed change.

20.7 Discussion

Statistical reasoning and methods are fundamental to the problem of detecting and attributing human influence on the climate. This is, in a sense, the ultimate small sample problem since there is only one realization of historical observed change, and consequently there is a very heavy reliance on physical understanding and climate models. The climate models provide physically based estimates of the expected climatic effects of external forcing and information that is used to describe the climate's natural internal variability. Physical process understanding is required to support statistical inferences about the presence or absence of the effects of external forcing on our climate.

While detection and attribution analyses involve complex physical reasoning and a series of complex data processing decisions, relatively simple statistical models have been used to make inferences about the presence and magnitude of externally forced effects on our climate. A number of assumptions, however, are made in the course of conducting an analysis. These assumptions include:

a) An assumption that the effects of different forcings acting on the climate system are additive. Perturbation analyses suggest that this is reasonable for small amounts of forcing, such as the forcing experienced to date. Nevertheless, there is some evidence that additivity may not hold in all cases, such as for precipitation at smaller than continental scales. This is because the effects on precipitation presumably result from a combination of thermodynamic (warming related) and dynamic (atmospheric circulation related) changes.

b) An assumption that forcing does not affect the natural internal variability of the climate system. Again, this should be true for small forcings, although some studies have demonstrated, for example, that the extremes of temperature may not change in step with changes in the mean of the surface temperature distribution under projected future forcing in all locations; see, e.g., Hegerl et al. (2004) or Kharin et al. (2013).

c) A strong assumption that modern climate models simulate the natural internal variability of the climate system well. The evidence suggests, overall, that models do simulate internal variability well on the space and time scales considered in detection and attribution studies; see, e.g., Hegerl et al. (2007) or Jones et al. (2013). Also, detection and attribution studies routinely compare residual variability to model simulated internal variability; see, e.g., Allen and Stott (2003) and Ribes et al. (2013).

d) A further strong assumption is that the collection of climate models participating in experiments such as CMIP5 can be thought of as a sample that has been drawn from a defined population with a known sampling strategy. While this is not at all an obvious assumption (Rougier et al., 2010; von Storch and Zwiers, 2013), empirical evidence suggests, for example, that currently available climate models have biases that cluster about zero; see, e.g., Gleckler et al. (2008), Jun et al. (2008) and Sillmann et al. (2013). Designed experiments that control the sources of variation between different climate models, for example, to quantify the uncertainty from uncertain parameters are beginning to be used; see, e.g., Murphy et al. (2004), Stainforth et al. (2005), and subsequent literature. However, these types of approaches to uncertainty quantification have not yet permeated to the large-scale coordinated modeling protocols, such as that of CMIP5.

Each of these assumptions represents an important ongoing area of climate research. Detection and attribution studies acknowledge these limitations, and high-level assessments of the literature, such as those of the Intergovernmental Panel on Climate Change (Hegerl et al., 2007), take them into account when evaluating the available body of science.

Finally, a critical element in detection and attribution is the estimation of the covariance characteristics of the climate's natural internal variability. Up until recently, climate scientists have used sample covariance matrices calculated from samples of climate model output rather than more advanced approaches, e.g., the use of so-called shrinkage estimators such as that of Ledoit and Wolf (2004). While such approaches, as adopted for example by Ribes and Terray (2013), alleviate a technical issue, they bring into clearer focus the question of how observations should be processed prior to conducting a formal detection and attribution analysis. Such pre-processing should isolate, in a transparent way, the spacial and temporal scales at which we expect signals to be evident and also should be designed to retain only scales on which models are judged to be reliable, which is an assessment that remains challenging; see, e.g., Knutti et al. (2010).

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