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Detection and attribution methodologies overview (APPENDIX C)

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Abstract

In this appendix, we present a brief overview of the methodologies and methodological issues for detection and attribution of climate change. Attributing an observed change or an event partly to a causal factor (such as anthropogenic climate forcing) normally requires that the change first be detectable (Hegerl et al. 2010). A *detectable* observed change is one which is determined to be highly unlikely to occur (less than about a 10% chance) due to internal variability alone, without necessarily being ascribed to a causal factor. An *attributable* change refers to a change in which the relative contribution of causal factors has been evaluated along with an assignment of statistical confidence (e.g., Bindoff et al. 2013; Hegerl et al. 2010).

As outlined in Bindoff et al. (2013), the conceptual framework for most detection and attribution studies consists of four elements: 1) relevant observations; 2) the estimated time history of relevant climate forcings (such as greenhouse gas concentrations or volcanic activity); 3) a modeled estimate of the impact of the climate forcings on the climate variables of interest; and 4) an estimate of the internal (unforced) variability of the climate variables of interest—that is, the changes that can occur due to natural unforced variations of the ocean, atmosphere, land, cryosphere, and other elements of the climate system in the absence of external forcings. The four elements above can be used together with a detection and attribution framework to assess possible causes of observed changes.

Appendix C. Detection and Attribution Methodologies Overview

C.1 Introduction and Conceptual Framework

In this appendix, we present a brief overview of the methodologies and methodological issues for detection and attribution of climate change. Attributing an observed change or an event partly to a causal factor (such as anthropogenic climate forcing) normally requires that the change first be detectable (Hegerl et al. 2010). A *detectable* observed change is one which is determined to be highly unlikely to occur (less than about a 10% chance) due to internal variability alone, without necessarily being ascribed to a causal factor. An *attributable* change refers to a change in which the relative contribution of causal factors has been evaluated along with an assignment of statistical confidence (e.g., Bindoff et al. 2013; Hegerl et al. 2010).

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C.2 Fingerprint-Based Methods

A key methodological approach for detection and attribution is the regression-based "fingerprint" method (e.g., Hasselmann 1997; Allen and Stott 2003; Hegerl et al. 2007; Hegerl and Zwiers 2011; Bindoff et al. 2013), where observed changes are regressed onto a model-generated response pattern to a particular forcing (or set of forcings), and regression scaling factors are obtained. When a scaling factor for a forcing pattern is determined to be significantly different from zero, a detectable change has been identified. If the uncertainty bars on the scaling factor encompass unity, the observed change is consistent with the modeled response, and the observed change can be attributed, at least in part, to the associated forcing agent, according this methodology. Zwiers et al. (2011) showed how detection and attribution methods could be applied to the problem of changes in daily temperature extremes at the regional scale by using a generalized extreme value (GEV) approach. In their approach, a time-evolving pattern of GEV location parameters (i.e., "fingerprint") from models is fit to the observed extremes as a means of detecting and attributing changes in the extremes to certain forcing sets (for example, anthropogenic forcings).

A recent development in detection/attribution methodology (Ribes et al. 2017) uses hypothesis testing and an additive decomposition approach rather than linear regression of patterns. The new approach makes use of the magnitudes of responses from the models rather than using the model patterns and deriving the scaling factors (magnitudes of responses) from regression. The new method, in a first application, gives very similar attributable anthropogenic warming estimates to the earlier methods as reported in Bindoff et al. (2013) and shown in Figure 3.2. Some further methodological developments for performing optimal fingerprint detection and attribution studies are proposed in Hannart (2016), who, for example, focuses on the possible use of raw data in analyses without the use of dimensional reductions, such as projecting the data onto a limited number of basis functions, such as spherical harmonics, before analysis.

C.3 Non-Fingerprint Based Methods

A simpler detection/attribution/consistency calculation, which does not involve regression and pattern scaling, compares observed and simulated time series to assess whether observations are consistent with natural variability simulations or with simulations forced by both natural and anthropogenic forcing agents (Knutson et al. 2013; van Oldenborgh et al. 2013). Cases where observations are inconsistent with model simulations using natural forcing only (a detectable change), while also being consistent with models that incorporate both anthropogenic and natural forcings, are interpreted as having an attributable anthropogenic contribution, subject to caveats regarding uncertainties in observations, climate forcings, modeled responses, and simulated internal climate variability. This simpler method is useful for assessing trends over smaller regions such as sub-regions of the United States (see the example given in Figure 6.5 for regional surface temperature trends).

Delsole et al. (2011) introduced a method of identifying internal (unforced) variability in climate data by decomposing variables by timescale, using a measure of their predictability. They found that while such internal variability could contribute to surface temperature trends of 30-years' duration or less, and could be responsible for the accelerated global warming during 1977–2008 compared to earlier decades, the strong (approximately 0.8°C, or 1.4°F) warming trend seen in observations over the past century was not explainable by such internal variability. Constructed circulation analogs (van den Dool et al. 2003; Deser et al. 2016) is a method used to identify the part of observed surface temperature changes that is due to atmospheric circulation changes alone.

The timescale by which climate change signals will become detectable in various regions is a question of interest in detection and attribution studies, and methods of estimating this have been developed and applied (e.g., Mahlstein et al. 2011; Deser et al. 2012b). These studies illustrate how natural variability can obscure forced climate signals for decades, particularly for smaller (less than continental) space scales.

Other examples of detection and attribution methods include the use of multiple linear regression with energy balance models (e.g., Canty et al. 2013) and Granger causality tests (e.g., Stern and Kaufmann 2014). These are typically attempting to relate forcing time series, such as the historical record of atmospheric CO_2 since 1860, to a climate response measure, such as global mean temperature or ocean heat content, but without using a full coupled climate model to explicitly estimate the response of the climate system to forcing (or the spatial pattern of the response to forcing). Granger causality, for example, explores the lead–lag relationships between different variables to infer causal relationships between them, and attempts to control for any influence of a third variable that may be linked to the other two variables in question.

C.4. Multistep Attribution and Attribution without Detection

A growing number of climate change and extreme event attribution studies use a *multistep attribution* approach (Hegerl et al. 2010), based on attribution of a change in climate conditions that are closely related to the variable or event of interest. In the multistep approach, an observed change in the variable of interest is attributed to a change in climate or other environmental conditions, and then the changes in the climate or environmental conditions are separately attributed to an external forcing, such as anthropogenic emissions of greenhouse gases. As an example, some attribution statements for phenomena such as droughts or hurricane activity—where there are not necessarily detectable trends in occurrence of the phenomenon itself—are based on models and on detected changes in related variables such as surface temperature, as well as an understanding of the relevant physical processes linking surface temperatures to hurricanes or drought. For example, some studies of the recent California drought (e.g., Mao et al. 2015; Williams et al. 2015) attribute a fraction of the event to anthropogenic warming or to long-term warming based on modeling or statistical analysis, although without claiming that there was a detectable change in the drought frequency or magnitude.

The multistep approach and model simulations are both methods that, in principle, can allow for attribution of a climate change or a change in the likelihood of occurrence of an event to a causal factor without necessarily detecting a significant change in the occurrence rate of the phenomenon or event itself (though in some cases, there may also be a detectable change in the variable of interest). For example, Murakami et al. (2015) used model simulations to conclude that the very active hurricane season observed near Hawai‘i in 2014 was at least partially attributable to anthropogenic influence; they also show that there is no clear long-term detectable trend in historical hurricane occurrence near Hawai‘i in available observations. If an attribution statement is made where there is not a detectable change in the phenomenon itself (for example, hurricane frequency or drought frequency) then this statement is an example of *attribution without detection*. Such an attribution without detection can be distinguished from a conventional single-step attribution (for example, global mean surface temperature) where in the latter case there is a detectable change in the variable of interest (or the scaling factor for a forcing pattern is significantly different from zero in observations) and attribution of the changes in that variable to specific external forcing agents. Regardless of whether a single-step or multistep attribution approach is used, or whether there is a detectable change in the variable of interest, attribution statements with relatively higher levels of confidence are underpinned by a thorough understanding of the physical processes involved.

There are reasons why attribution without detection statements can be appropriate, despite the lower confidence typically associated with such statements as compared to attribution statements that are supported by detection of a change in the phenomenon itself. For example, an event of interest may be so rare that a trend analysis for similar events is not practical. Including attribution without detection events in the analysis of climate change impacts reduces the chances of a false negative, that is, incorrectly concluding that climate change had no influence on a given extreme events (Anderegg et al. 2014) in a case where it did have an influence. However, avoiding this type of error through attribution without detection comes at the risk of increasing the rate of false positives, where one incorrectly concludes that anthropogenic climate change had a certain type of influence on an extreme event when in fact it did not have such an influence (see Box 3.1).

C.5 Extreme Event Attribution Methodologies

Since the release of the Intergovernmental Panel on Climate Change's Fifth Assessment Report (IPCC AR5) and the Third National Climate Assessment (NCA3; Melillo et al. 2014), there have been further advances in the science of detection and attribution of climate change. An emerging area in the science of detection and attribution is the attribution of extreme weather and climate events (NAS 2016; Stott 2016; Easterling et al. 2016). According to Hulme (2014), there are four general types of attribution methods that are applied in practice: physical reasoning, statistical analysis of time series, fraction of attributable risk (FAR) estimation, and the philosophical argument that there are no longer any purely natural weather events. As discussed in a recent National Academy of Sciences report (NAS 2016), possible anthropogenic influence on an extreme event can be assessed using a risk-based approach, which examines whether the odds of occurrence of a type of extreme event have changed, or through an ingredients-based or conditional attribution approach.

In the risk-based approach (Stott et al. 2004; Hulme 2014; NAS 2016), one typically uses a model to estimate the probability (p) of occurrence of a weather or climate event within two climate states: one state with anthropogenic influence (where the probability is p_1) and the other state without anthropogenic influence (where the probability is p_0). Then the ratio (p_1/p_0) describes how much more or less likely the event is in the modeled climate with anthropogenic influence compared to a modeled hypothetical climate without anthropogenic influences. Another common metric used with this approach is the fraction of attributable risk (FAR), defined as $FAR = 1–(p_0/p_1)$. Further refinements on such an approach using causal theory are discussed in Hannart et al. (2016b).

In the conditional or ingredients-based approach (Trenberth et al. 2015; Shepherd 2016; Horton et al. 2016; NAS 2016), an investigator may look for changes in occurrence of atmospheric circulation and weather patterns relevant to the extreme event, or at the impact of certain environmental changes (for example, greater atmospheric moisture) on the character of an extreme event. Conditional or ingredients-based attribution can be applied to extreme events or to climate changes in general. An example of the ingredients-based approach and more discussion of this type of attribution method is given in Box C.2.

Hannart et al. (2016b) have discussed how causal theory can also be applied to attribution studies in order to distinguish between necessary and sufficient causation. Hannart et al. (2016a) further propose methodologies to use data assimilation systems, which are now used operationally to update short-term numerical weather prediction models, for detection and attribution. They envision how such systems could be used in the future to implement near-real time systematic causal attribution of weather and climate-related events.

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Box C.1. On the Use of Significance Levels and Significance Tests in Attribution Studies

In detection/attribution studies, a detectable observed change is one which is determined to be highly unlikely to occur (less than about a 10% chance) due to internal variability alone. Some frequently asked questions concern the use of such a high statistical threshold (significance level) in attribution studies. In this box, we respond to several such questions received in the public review period.

- Why is such a high degree of confidence (for example, statistical significance at *p* level of 0.05) typically required before concluding that an attributable anthropogenic component to a climate change or event has been detected? For example, could attribution studies be reframed to ask whether there is a 5% or more chance that anthropogenic climate change contributed to the event?

This question is partly related to the issue of risk avoidance. For example, if there is a particular climate change outcome that we wish to avoid (for example, global warming of 3°C, or 10°C, or a runaway greenhouse) then one can use the upper ranges of confidence intervals of climate model projections as guidance, based on available science, for avoiding such outcomes. Detection/attribution studies typically deal with smaller changes than climate projections over the next century or more. For detection/attribution studies, researchers are confronting models with historical data to explore whether or not observed climate change signals are emerging from the background of natural variability. Typically the emergent signal is just a small fraction of what is predicted by the models for the coming century under continued strong greenhouse gas emission scenarios. Detecting that a change has emerged from natural variability is not the same as approaching a threshold to be avoided, unless the goal is to ensure no detectable anthropogenic influence on climate. Consequently, use of a relative strong confidence level (or *p*-value of 0.05) for determining climate change detection seems justified for the particular case of climate change detection, since one can also separately use risk-avoidance strategies or probability criteria to avoid reaching certain defined thresholds (for example, a 2°C global warming threshold).

A related question concerns ascribing blame for causing an extreme event. For example, if a damaging hurricane or typhoon strikes an area and causes much damage, affected residents may ask whether human-caused climate change was at least partially to blame for the event. In this case, climate scientists sometimes use the "Fraction of Attributable Risk" framework, where they examine whether the odds of some threshold event occurring have been increased due to anthropogenic climate change. This is typically a model-based calculation, where the probability distribution related to the event in question is modeled under preindustrial and present-day climate conditions, and the occurrence rates are compared for the two modeled distributions. Note that such an analysis can be done with or without the detection of a climate change signal for the occurrence of the event in question. In general, cases where there has been a detection and attribution of changes in the event in question to human causes, then the attribution of increased risk to anthropogenic forcing will be relatively more confident.

The question of whether it is more appropriate to use approaches that incorporate a high burden of statistical evidence before concluding that anthropogenic forcings contributed significantly (as in traditional detection/attribution studies) versus using models to estimate anthropogenic contributions when there may not even be a detectable signal present in the observations (as in some Fraction of Attributable Risk studies) may depend on what type of error or scenario one most wants to avoid. In the former case, one is attempting to avoid the error of concluding that anthropogenic forcing has contributed to some observed climate change, when in fact, it later turns out that anthropogenic forcing has not contributed to the change. In the second case, one is attempting to avoid the "error" of concluding that anthropogenic forcing has not contributed significantly to an observed climate change or event when (as it later comes to be known) anthropogenic forcing had evidently contributed to the change, just not at a level that was detectable at the time compared to natural variability.

- What is the tradeoff between false positives and false negatives in attribution statistical testing, and how is it decided which type of error one should focus on avoiding?

As discussed above, there are different types of errors or scenarios that we would ideally like to avoid. However, the decision of what type of analysis to do may involve a tradeoff where one decides that it is more important to avoid either falsely concluding that anthropogenic forcing *has* contributed, or to avoid falsely concluding that anthropogenic forcing had *not* made a detectable contribution to the event. Since there is no correct answer that can apply in all cases, it would be helpful if, in requesting scientific assessments, policymakers provide some guidance about which type of error or scenario they would most desire be avoided in the analyses and assessments in question.

- Since substantial anthropogenic climate change (increased surface temperatures, increased atmospheric water vapor, etc.) has already occurred, aren't all extreme events affected to some degree by anthropogenic climate change?

Climate scientists are aware from modeling experiments that very tiny changes to initial conditions in model simulations lead to very different realizations of internal climate variability "noise" in the model simulations. Comparing large samples of this random background noise from models against observed changes is one way to test whether the observed changes are statistically distinguishable from internal climate variability. In any case, this experience also teaches us that any anthropogenic influence on climate, no matter how tiny, has some effect on the future trajectory of climate variability, and thus could affect the timing and occurrence of extreme events. More meaningful questions are: 1) Has anthropogenic forcing produced a statistically significant change in the probability of occurrence of some class of extreme event? 2) Can we determine with confidence the net sign of influence of anthropogenic climate change on the frequency, intensity, etc., of a type of extreme event? 3) Can climate scientists quantify (with credible confidence intervals) the effect of climate change on the occurrence frequency, the intensity, or some other aspect of an observed extreme event?

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Box C.2 Illustration of Ingredients-based Event Attribution: The Case of Hurricane Sandy

To illustrate some aspects of the conditional or ingredients-based attribution approach, the case of Hurricane Sandy can be considered. If one considers Hurricane Sandy's surge event, there is strong evidence that sea level rise, at least partly anthropogenic in origin (see Ch. 12: Sea Level Rise), made Sandy's surge event worse, all other factors being equal (Reed et al. 2015). The related question of whether anthropogenic climate change increased the risk of an event like Sandy involves not just the sea level ingredient to surge risk but also whether the frequency and/or intensity of Sandy-like storms has increased or decreased as a result of anthropogenic climate change. This latter question is more difficult and is briefly reviewed here.

A conditional or ingredients-based attribution approach, as applied to a hurricane event such as Sandy, may assume that the weather patterns in which the storm was embedded—and the storm itself—could have occurred in a preindustrial climate, and the event is re-simulated while changing only some aspects of the large-scale environment (for example, sea surface temperatures, atmospheric temperatures, and moisture) by an estimated anthropogenic climate change signal. Such an approach thus explores whether anthropogenic climate change to date has altered the odds of occurrence or intensity of a Hurricane Sandy-like event. Modeling studies show, as expected, that the anomalously warm sea surface temperatures off the U.S. East Coast during Sandy led to a substantially more intense simulated storm than under present-day climatological conditions (Magnusson et al. 2014). However, these anomalous sea surface temperatures and other environmental changes are a mixture of anthropogenic and natural influences, and so it is not generally possible to infer the anthropogenic component from such experiments. Another study (Lackmann 2015) modeled the influence of just the anthropogenic changes to the thermodynamic environment (including sea surface temperatures, atmospheric temperatures, and moisture perturbations) and concluded that anthropogenic climate change to date had caused Hurricane Sandy to be about 5 hPa more intense, but that this modeled change was not statistically significant at the 95% confidence level. A third study used a statistical–dynamical model to compare simulated New York City-area tropical cyclones in pre-anthropogenic and anthropogenic time periods (Reed et al. 2015). It concluded that there have been anthropogenically induced increases in the types of tropical cyclones that cause extreme surge events in the region, apart from the effects of sea level rise, such as increased radius of maximum winds in the anthropogenic era. However, the statistical–dynamical model used in the study simulates an unusually large increase in global tropical cyclone activity in 21st century projections (Emanuel 2013) compared to other tropical cyclone modeling studies using dynamical models—a number of which simulate future decreases in late 21st century tropical storm frequency in the Atlantic basin (e.g., Christensen et al. 2013). This range of uncertainty among various model simulations of Atlantic tropical cyclone activity changes under climate change imply that there is low confidence in determining the net impact to date of anthropogenic climate change on the risk of Sandy-like events, though anthropogenic sea level rise, all other things equal, has increased the surge risk.

In summary, while there is agreement that sea level rise alone has caused greater storm surge risk in the New York City area, there is low confidence on whether a number of other important determinants of storm surge climate risk, such as the frequency, size, or intensity of Sandy-like storms in the New York region, have increased or decreased due to anthropogenic warming to date.

----- END BOX C.2 HERE -----

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