Advanced Review

Use of models in detection and attribution of climate change

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Most detection and attribution studies use climate models to determine both the expected 'fingerprint' of climate change and the uncertainty in the estimated magnitude of this fingerprint in observations, given the climate variability. This review discusses the role of models in detection and attribution, the associated uncertainties, and the robustness of results. Studies that use observations only make substantial assumptions to separate the components of observed changes due to radiative forcing from those due to internal climate variability. Results from observation-only studies are broadly consistent with those from fingerprint studies. Fingerprint studies evaluate the extent to which patterns of response to external forcing (fingerprints) from climate model simulations explain observed climate change *in observations*. Fingerprints are based on climate models of various complexities, from energy balance models to full earth system models. Statistical approaches range from simple comparisons of observations with model simulations to multi-regression methods that estimate the contribution of several forcings to observed change using a noise-reducing metric. Multi-model methods can address model uncertainties to some extent and we discuss how remaining uncertainties can be overcome. The increasing focus on detecting and attributing regional climate change and impacts presents both opportunities and challenges. Challenges arise because internal variability is larger on smaller scales, and regionally important forcings, such as from aerosols or land-use change, are often uncertain. Nevertheless, if regional climate change can be linked to external forcing, the results can be used to provide constraints on regional climate projections.
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INTRODUCTION

Since the mid-1990s, a wide range of studies have shown that anthropogenic greenhouse gas increases have influenced the climate, globally and regionally, affecting many variables (see Refs 1 and 2 for reviews). However, even to scientists, the role of observations, physical insight, and climate models in estimates of the human contribution to recent climate change is not always clear. For example, some of the discussions of Figure 2 (which is from Refs 2 and 3) and Ref 4 fail to recognize that uncertainties in climate model sensitivity or the amplitude of aerosol forcing have little bearing on estimates of the contribution by greenhouse gases to recent warming. We discuss here the role of models in our understanding of the causes of climate change, review open questions and major uncertainties, particularly those due to model uncertainty, and discuss ways forward.

Detection and attribution methods attempt to separate the observed climate changes into components that can be explained by variability generated within the climate system and components that result from changes external to the climate system. Examples for the latter include changes in the earth's energy budget due to increasing greenhouse gas concentrations, affecting outgoing infrared radiation, or changes in incoming solar radiation. Changes in the radiative budget of the planet are called 'radiative forcing'. Detection and attribution has multiple goals: The initial focus was on determining whether the radiative forcing due to greenhouse gas increases has indeed influenced climate. Subsequently, it has been understood that detection and attribution methods

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also objectively evaluate the ability of climate models to simulate observed climate change, assess the role of external factors versus climate variability in observed climate change, and enable prediction of future climate change that is grounded in changes observed so far.[5,6]

Before discussing model reliance and uncertainty, it is worth mentioning that detection and attribution studies are affected by uncertainties beyond modeling. Observations are subject to uncertainty, and ideally, results need to address this uncertainty either by using several independently developed compilations of observed changes[7] or by estimating the effect of observational uncertainties (Ref 8 assessed the effect of random sampling uncertainty, while systematic uncertainty, for example due to bucket corrections applied to sea surface temperature, is more difficult to assess[9]). Another important uncertainty affecting the accuracy of model simulations is radiative forcing uncertainty. Forcing uncertainty is generally understood to be small in the case of well-mixed greenhouse gases[10] that have well understood effects on the planet's radiative balance. Uncertainties are larger for other types of anthropogenic forcing, including aerosol forcing and forcing from land-use changes, such as consequences from the conversion of forest to agricultural land.[10] The forcing picture is further complicated because of feedback processes that may either amplify or damp the direct effect of a given forcing agent. For example, the emission of aerosols into the atmosphere may alter cloud microphysical properties so as to increase cloud reflectivity and/or cloud lifetime, both of which would reduce the amount of solar energy reaching the surface, thereby inducing an uncertain cooling effect on the climate.[10] Our understanding of how aerosols affect cloud microphysical properties remains limited at this stage. The climate is also influenced by natural forcing agents, including episodic volcanic activity and variations in the amount of energy that is emitted by the sun. Explosive volcanic eruptions that eject reflective material (dust and aerosols) into the stratosphere affect climate by reducing the amount of sunlight that reaches the surface. This has a short-term effect on climate[11] in the order a few years, and may have a long-term effect leading to cooling during multi-decade periods with greater amounts of volcanic activity.[12,13] The recent history of volcanic forcing is well understood, whereas forcing prior to the 20th century has greater uncertainty, particularly with respect to the magnitude of individual eruptions.[14] Solar forcing influences climate on a number of timescales, which are, prior to the satellite era, indirectly (and incompletely) indicated by sunspot number and by variations in the production of various types of isotopes in the earth system.[15,16] Estimates of solar forcing, particularly for the pre-satellite era, remain uncertain. These uncertainties need to be kept in mind when relating climate model results to observations.

The remainder of this review is organized as follows. We first consider approaches that avoid using models for distinguishing the response to external forcing, particularly greenhouse gas increases. The discussion shows that such a separation requires substantial assumptions and thus motivates the use of some form of climate model to derive an estimate of the expected change in response to an external forcing. The subsequent section discusses detection and attribution methods using climate models. This is followed by a section that discusses results based on first simple and then complex climate models, a section discussing the consequences of model uncertainty on detection and attribution, and a section on difficulties encountered when addressing regional climate change.

OBSERVATION-ONLY METHODS FOR IDENTIFYING THE ANTHROPOGENIC SIGNAL

Some work has, explicitly or implicitly, attempted to distinguish anthropogenic or other externally forced climate change from observations only. While it is attractive to try to avoid models, substantial assumptions are required to separate an externally driven change from variability based on observations only.

Methods Using Spatial Patterns to Separate Between Variability and External Forcing

Wallace et al.[17] observed that a large fraction of hemispheric mean wintertime variability in the Northern Hemisphere is associated with a pattern of anomalies over land and ocean of opposite signs, referred to as the 'Cold Ocean Warm Land (COWL)' pattern. This pattern originates because strong wintertime dynamics, for example, associated with stronger or weaker than average westerlies, moves more or less heat from the ocean mixed layer to land, leading to positive or negative anomalies of the Northern Hemispheric mean temperature. By filtering out variations associated with this pattern, a remaining trend in large-scale temperature can be identified that is less affected by wintertime dynamic variability and hence may reflect more clearly the response to forcing. This technique was recently applied to sea surface temperature data[18] and led to the identification of an inhomogeneity in sea surface temperature data in the mid-20th century. The result also shows a long-term warming that appears

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to have been externally forced and a short-term cooling caused by volcanic eruptions (Figure 1, top).[18] While this method is well suited for detecting an underlying globally uniform change, a weakness is that the COWL temperature pattern correlates with the pattern of stronger warming over land than oceans which is anticipated from the greenhouse warming fingerprints in models. Thompson et al.[18] deal with this in part by defining a COWL pattern in terms of sea level pressure, which is less strongly affected by anthropogenic forcing than temperature, although there is also some evidence of human influence on the sea level pressure distribution.[19]

A number of further studies have analyzed, for example, by empirical orthogonal functions (EOFs), the evolution of observed global-scale surface or sea surface temperature. One of the first few EOFs is often associated with a long-term trend.[20] that does not appear to be internal to the climate system. However, EOFs may confound multiple aspects of change from different physical processes that are associated with long timescales. Spatial associations of observed patterns of change can also be used to analyze data in search for physical mechanisms of a changing climate. An example is Portmann et al.,[21] who associate locations with high or low climatological precipitation with locations where the maximum daily temperature increases or decreases, and then show that this spatial association is stronger than expected by random variability early in the growing season. This is an example of using the spatial and temporal characteristics of an unexplained change (here, the lack of warming in the warm tail of daytime maximum temperature in the South Eastern US) to suggest possible causes. However, only model simulations would be able to reliably confirm if hypothesized changes, for example, in biogenic aerosols in response to long-term changes in vegetation, can explain the observed lack of increase in hot extremes.

Methods Separating Signal and Noise Based on Timescales

Several studies have attempted to separate the influence of long-term external forcing from changes induced by short-term dynamics by focusing on timescale differences. A simple example is the identification of long-term trends in time series usually dominated by short-term dynamics (such as the positive trend in the Arctic Oscillation/Northern Annual Mode into the 1990s).[22] This approach can be carried over to more sophisticated methods, for example, methods that apply a prewhitening transform to climate records to detect 'unusual' patterns of change in time[23] (see review in Ref 24). Schneider and Held[25] use a closely related technique that discriminates between slow changes in climate and shorter timescale variability to identify in observations a pattern of surface temperature change associated with long timescales (Figure 1, bottom). These patterns show some similarity to model-simulated patterns of response to anthropogenic forcing, with peak warming over Eurasia and parts of North America in winter and a smooth time evolution. The authors speculate that regions of cooling in summer may be related to aerosol forcing, although it is also possible that aspects of these patterns are due to climate variability on long timescales. The method assumes that changes in external drivers, particularly greenhouse gas increases, lead to patterns that are statistically distinct from shorter-term patterns recorded due to variability generated within the climate system. However, internal climate variability is present on all timescales,[26] and thus the separation of anthropogenic change will be incomplete. This method also cannot separate between anthropogenic drivers and changes due to slowly varying external drivers of climate change, such as low-frequency solar radiation changes.

Methods Using Forcing History

A different approach is motivated by the fact that recent greenhouse gas levels far exceed previous levels ('The combined radiative forcing due to increases in carbon dioxide, methane, and nitrous oxide is $+2.30$ [$+2.07$ to $+2.53$] W m^{-2}, and its rate of increase during the industrial era is *very likely* to have been unprecedented in more than 10,000 years'[3,10]). This motivates comparisons between recent temperatures and reconstructions of large-scale temperatures over several centuries or millennia[27] to determine whether recent temperatures are also unusual. The Intergovernmental Panel on Climate Change (IPCC) concluded that the average Northern Hemisphere temperatures during the second half of the 20th century were '*very likely* higher than during any other 50-year period in the last 500 years and *likely* the highest in at least the past 1300 years', thus confirming the unusual nature of recent temperatures.[28] The 'likely' assessment accounts for large uncertainties in reconstructions of hemispheric temperatures based on incomplete sampling, unclear relationships between proxies and temperature, and questions about which data fully preserve low-frequency variability. However, a comparison of different climatic mean states is of limited use because climate variability and natural climate forcings combined can also produce changes in very long timescales[2,28] and because this method

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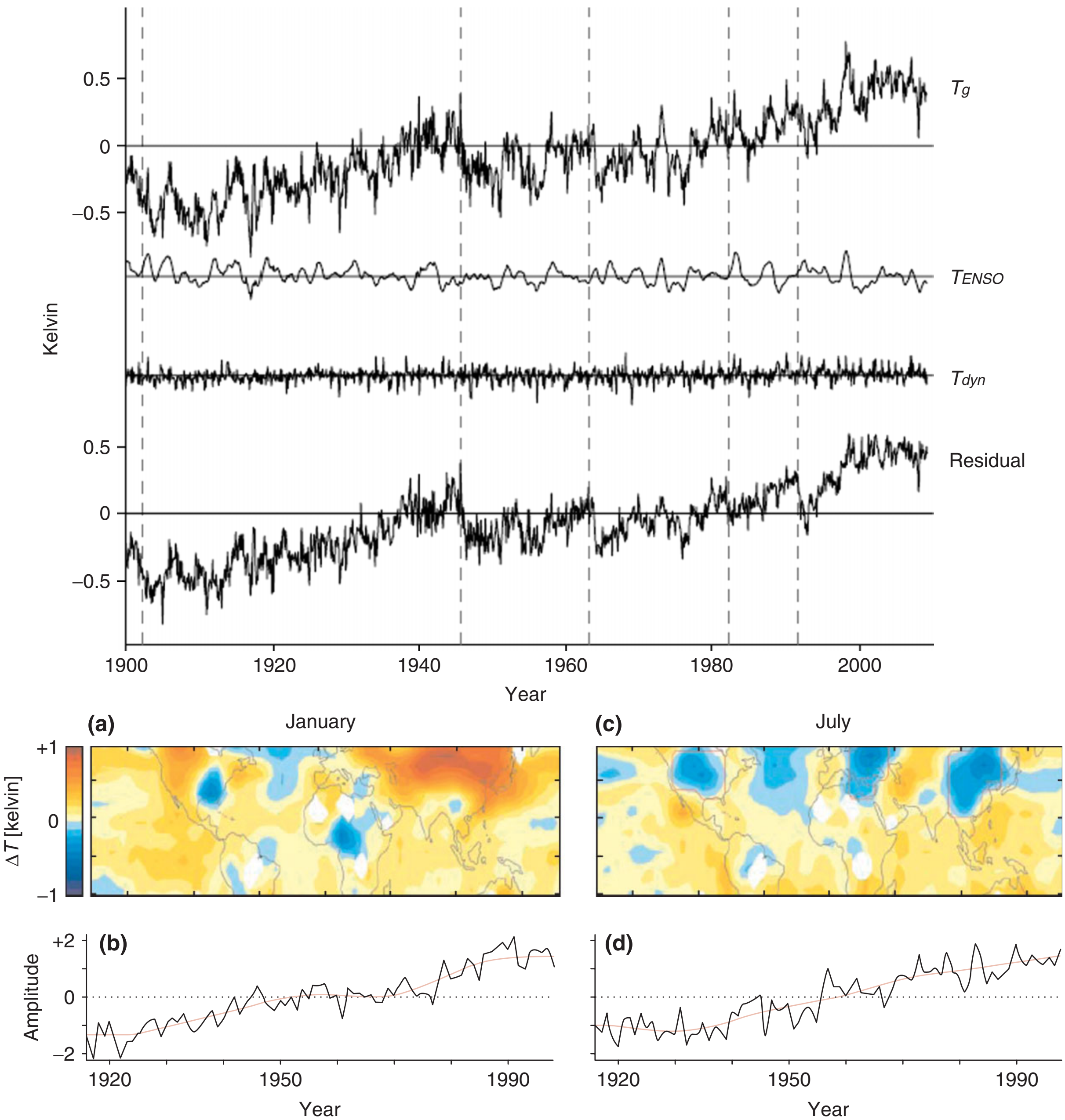

FIGURE 1 | Results of studies filtering externally driven signals based on observational data only. Top panel: a time series of global mean monthly surface temperature (topmost) is shown compared to contributions by variability from El Nino, short-term dynamical variations in extratropics (Tdyn), and the residual that remains after removing both (each time series is offset for presentation purposes; Reprinted with permission from Ref 18. Copyright 2009 American Meteorological Society). The vertical lines indicate August 1945 and the timing of volcanic eruptions. Bottom: First discriminants of interdecadal variations in (a) January and (c) July, based on separating climate variability between long and short timescales. Changes are expressed relative to the 1916–1998 mean. Upper panels (a) and (c): discriminant pattern. Lower panels (b) and (d): canonical variates, which give the time evolution. (Reprinted with permission from Ref 20. Copyright 2001 American Meteorological Society)

does not distinguish between climate change due to slow changes in radiative balance and the relatively rapid changes associated with greenhouse gas increases. Furthermore, such a comparison has limitations when forcing, such as from greenhouse gases, increases rapidly. In that case, a substantial part of the warming is not realized instantaneously. For example, Hansen et al.[29] point out that in their climate model, the response to 0.85 W m^{-2} of the recent greenhouse gas forcing is still 'in the pipeline', suggesting that there would be an estimated 0.6°C further warming even if immediate stabilization of the atmospheric

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composition was possible, consistent with Ref 3. Thus, comparing the medieval warm period with the present compares a climate state that was probably close to equilibrium with our present, rapidly evolving warming that is not yet fully realized. Therefore, while the present unusual warmth is suggestive, it is neither necessary nor sufficient to demonstrate that greenhouse gas increases have influenced climate.

A more quantitative approach to determining the role of external forcings in climate variations over the last millennium is to simultaneously correlate past greenhouse gas increases, volcanism, and solar forcing changes with reconstructed Hemispheric mean temperature changes.[30] The results indicate that the recent increase in temperature in the reconstruction is best explained by greenhouse gas increases. However, this method also has drawbacks because as above it does not account for the thermal inertia of climate components, particularly the ocean, which delay the response to forcing. This particularly affects the response to volcanic eruptions (see below), where the rapid short-lived forcing leads to a climate response of several years[11,31] that is not well characterized by the forcing time series.

In conclusion, while methods that do not use climate models directly avoid explicit assumptions about the shape and timing of the expected response, they do use other strong assumptions, such as the assumption that the response to forcing is instantaneous or that climate change and variability can be separated by timescale. Such methods therefore use implicit 'models' of the climate system's reaction to a change, for example that the response is proportional to radiative forcing, different in timescale, or otherwise separable. The fact that results from analyses based on observations only very often show similar results to those based on detection and attribution methods that use climate models lends strength to the overall assessment that the recent warming is largely due to greenhouse gas forcing.[3] Furthermore, observation-only studies can play an important role in identifying changes that are either not reliably simulated by climate models or whose forcings are not yet fully understood (such as in the case of Ref 21).

DETECTION AND ATTRIBUTION METHODS USING CLIMATE MODELS

The previous section motivates using some form of physically based climate model to derive an estimate of the expected change in response to an external forcing, and the use of 'fingerprint methods' that use model-simulated response patterns to quantify the role of external forcing in observed climate change. Thus, the next short section introduces detection and attribution methods.

Methods Comparing Climate Model Data with Observations

As the climate is not purely deterministic, but also displays chaotic variations due to the internal dynamics of the system, all observed changes in climate will be combinations of deterministic, externally driven changes and changes caused by internal climate dynamics. Thus, detection and attribution approaches need to account for differences between models and observations that are due to internal variability.

The simplest use of climate models is to compare the recent temperature evolution directly with climate model simulations. For example, one approach is to show that recently observed global warming is significantly stronger than model-based estimates of the internal variability of the climate system,[32,33] and thus, that the warming is detectably stronger than internal variability. Estimates of internal variability are largely based on models, as past observed climate variability includes the response to external drivers. As this inference relies directly upon estimates of the internal variability from climate models, it is subject to uncertainties discussed below.

Direct comparisons with climate model simulations have also been used to tentatively attribute recent temperature changes to a combination of anthropogenic and natural forcing. For example, Figure 2[2] shows that coupled climate models are able to largely reproduce the observed temporal evolution of global mean temperature (in the areas covered with observations) if both natural and anthropogenic forcings are included, while they fail to reproduce the warming in the recent decades without anthropogenic influences, particularly greenhouse gas increases. A similar method has been used to assess observed climate change in individual grid boxes[33,34] by comparing trends in observations with those in unforced model simulations and in anthropogenically forced simulations. For many grid boxes, the observations are again only consistent with simulations that include anthropogenic forcings, which is interpreted as indicating that anthropogenic forcing is needed to explain the data. Again, this agreement is subject to model uncertainty, which is large on grid box scales, and to the possibility of compensating errors.

It has been pointed out[4] that the sample of best-effort simulations available for the IPCC AR4 shown in Figure 2 does not fully span the space of combinations of external forcing (particularly aerosol

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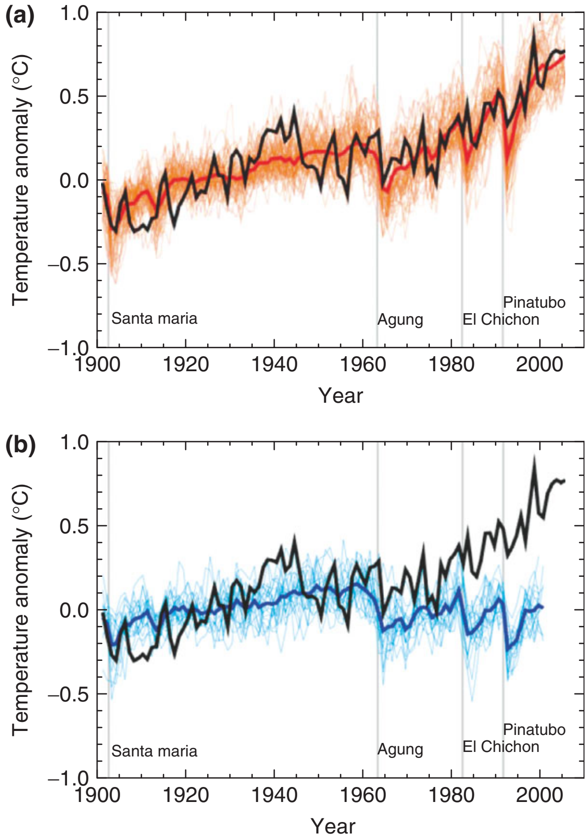

FIGURE 2 | Comparison between global mean temperature changes relative to the 1901–1950 average (°C) from observations (black) and simulated by climate model simulations that include (a) both human and natural influences on climate (for example, the effect of strong volcanic eruptions, marked by vertical gray bars) and (b) natural influences only. Individual model simulations are shown by thin lines, their average by a fat line (red in panel (a), blue in panel (b)). (Reprinted with permission from Ref 2. Copyright 2007 Cambridge University Press)

forcing) and climate sensitivity, raising the question: Is the agreement with data 'too good' and could there be compensating errors, for example, due to high climate sensitivity that is countered by too much indirect aerosol forcing? Fingerprint methods, which we discuss next, improve upon such simple comparisons by using both spatial and temporal information on climate change. Fingerprint methods can be used to estimate the contribution by individual signals separately, thus identifying, for example, if greenhouse warming in models is consistent with an estimate from observations or similarly, how the observationally estimated change due to aerosols compares to simulations. We will discuss below how this can help to fully describe the range of greenhouse gas and aerosol response that is consistent with the observations and hence address the possibility that the models shown in Figure 2 may not fully span uncertainties in the climate's sensitivity to forcing and our knowledge of aerosol forcing.

Fingerprint Methods

Fingerprint methods use the anticipated spatial, temporal, or space-time patterns of response to external forcing and determine whether these fingerprints are present in the observations and whether they are significantly stronger than expected from climate variability randomly projecting onto them. Thus, detection and attribution aims at distinguishing the externally driven changes from those that are internally generated.

Early work used pattern correlation statistics to obtain evidence of fingerprints in observations. Such studies calculate the spatial correlation between expected and observed patterns of climate change. For example, Santer et al.[35] calculated the correlation $c(t)$ of a fixed fingerprint pattern of expected climate change with time-averaged patterns of observed temperature change for consecutive blocks of time. The results showed that the correlation improved over time and that the trend in the resemblance between the patterns is greater than expected from internal variability. The latter is assessed by using blocks of climate model output with the same length and spatial coverage as the observations that are obtained from climate model 'control' simulations run without external forcing. A disadvantage of pattern correlation techniques is that they cannot be optimized to increase the detectability of the expected pattern of change or to effectively identify in observations the responses to more than one forcing agent simultaneously.

A general paradigm that is used either explicitly, for example, in optimal detection methods, or implicitly in pattern correlation methods, is that an observed climate change $\mathbf{y}$ is regarded as a linear combination of externally forced signals $\mathbf{X}$ and residual internal climate variability $\mathbf{u}$[36,37] (see also appendix of Ref 2):

$$\mathbf{y} = \mathbf{X}\mathbf{a} + \mathbf{u}. \qquad (1)$$

In this expression, vector $\mathbf{y}$ is a filtered version of the observed record (it can be the full space-time pattern of recent climate change or a subset of it), the columns of matrix $\mathbf{X}$ contain the estimated response patterns to the external forcings (signals) that are under investigation, and $\mathbf{a}$ is a vector of scaling factors which adjusts the amplitudes of those patterns, with one scaling factor for each fingerprint in matrix $\mathbf{X}$ (Figure 3). As shown in Figure 3, the model data used in this method are reduced to the coverage of observed data for a like-with like comparison. Vector $\mathbf{u}$ contains the regression residuals and represents internal climate variability. Vector $\mathbf{u}$ is usually assumed to be a Gaussian random vector with covariance matrix $\mathbf{C}$,

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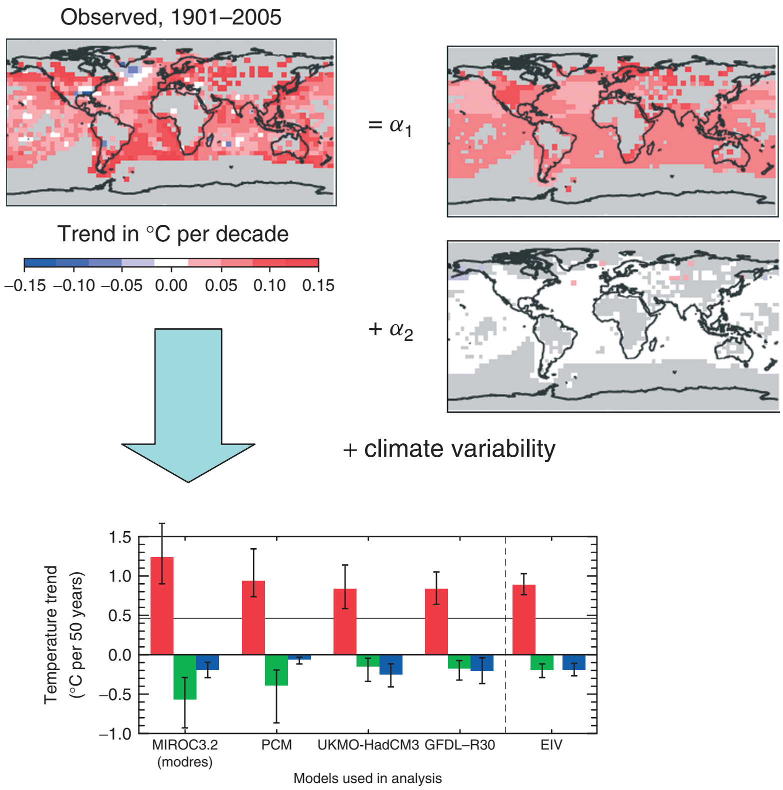

FIGURE 3 | Schematic for detection and attribution. The observed change (shown here: pattern of temperature change over the 20th century, left) is composed of a linear combination of fingerprints for all forcings combined (top, right) and for natural forcings only (center right, this combination allows rescaling of natural vs anthropogenic fingerprints in simulations of the 20th century) plus residual, unexplained variability. The resulting scaling factors and warming per fingerprint can be used to derive contributions to warming such as shown in the bottom panel, labeled panel (c), although in this instance the latter is derived from three fingerprints. It shows attributable warming estimated from a detection and attribution analysis for the 20th century, using a fingerprint of the spatial pattern and time evolution of climate change forced by greenhouse gases (red), other anthropogenic forcing (green), and solar and volcanic forcings combined (blue). The best estimate contribution of each forcing to warming in the 50-year period 1950–1999 is given by the vertical bar and the 5–95% uncertainty in that estimate is given by the black whiskers. The observed trend over that period is shown by a black horizontal line. The different estimates are derived using fingerprints from different models. (Reprinted with permission from Ref 2. Copyright 2007 Cambridge University Press)

although this assumption is not necessary to make statistical inferences about the scaling factors. It can be shown that a best (in a least square sense) linear unbiased estimator (BLUE) of the vector of scaling factors is given by

$$\mathbf{a} = (\mathbf{X}^{\mathrm{T}}\mathbf{C}^{-1}\mathbf{X})^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{C}^{-1}\mathbf{y} = (\tilde{\mathbf{X}}^{\mathrm{T}}\tilde{\mathbf{X}})^{-1}\tilde{\mathbf{X}}^{\mathrm{T}}\tilde{\mathbf{y}}. \quad (2)$$

Matrix $\tilde{\mathbf{X}}$ and vector $\tilde{\mathbf{y}}$ represent the signal patterns and observations after normalization by the climate's internal variability. The normalization transform maximizes the signal-to-noise ratio.[2,36,37] However, it is also possible to omit the use of the inverse covariance and use the Unit matrix instead, in a regular Euclidean regression approach.[12,36,38,39]

Uncertainty in the vector of scaling factors is estimated either by repeatedly superimposing samples of internal variability on the observations or by estimating ranges of scaling factors from fingerprints that can be caused by analyzing samples of internal climate variability.

Most recent detection and attribution work uses fingerprints that vary in time and space. These fingerprints are almost always obtained from climate models, particularly, Atmosphere-Ocean General Circulation Models (AOGCMS). AOGCMs consist of an atmospheric and an oceanic general circulation model, based on first principles of thermo- and fluid dynamics, together with sea-ice and land surface models, and augmented by approximations (called parameterizations) for processes that cannot be realistically simulated at the given resolution of approximately one to several degrees latitudinally and longitudinally.[40] Some recent models also contain interactive vegetation, carbon cycle and chemistry, and dynamic representations of the large ice sheets

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on Greenland and Antarctica, moving toward an earth system model. Because AOGCMs simulate natural internal variability as well as the response to specified anomalous external forcing, climate signals are typically estimated by averaging across an ensemble of AOGCM simulations to reduce the effects of internal variability on the signal estimates or fingerprints (for a discussion of optimal ensemble size and composition, see Ref 41). When ensembles are small or signals weak, the noise remnants in the fingerprints may bias ordinary least squares estimates downward. This can be avoided by estimating a with the total least squares (TLS) algorithm, which accounts for noise in the fingerprints.[42]

The vector **a** accounts for possible errors in the amplitudes of the external forcing and the climate model's response by scaling the signal patterns to best match the observations. If a chosen uncertainty range (e.g., 5–95%) does not include '0', this indicates that the fingerprint is likely present in observations and hence detectable. If the signal is detected, but the estimated uncertainty range does not include '1', this indicates that the model response has to be rescaled to match the observations. The model fingerprint, scaled with the range of scalings, thus provides an estimate of the range of forcing responses that are consistent with the observed change. This is shown in Figure 3, where the bar diagram results from scaling the model's warming over the recent 50 years in response to different external forcing by the range of scaling factors (best guess shown by bar, range by whiskers) that is consistent with the observations. Thus, even if a model's sensitivity was overestimated or its aerosol forcing underestimated, the estimated scaling factor would correct for this. This is why fingerprint methods can yield more rigorous and complete assessments of the cause of observed changes than methods that assess whether climate model simulations are consistent with the observations, given the natural variability. The scaling that has thus been estimated for greenhouse gas forcing can further be used for probabilistic predictions of future change that is anchored in observations.[5,43]

Use of the BLUE estimator is particularly helpful if the signal-to-noise ratio of forced signals to internal variability is low or if several signals are to be separated from each other and noise, improving the power of the method substantially. Application of the BLUE estimator requires an estimate of the covariance matrix **C** (i.e., the internal variability) and its inverse. This is usually obtained from unforced variation simulated by AOGCMs (e.g., from long control simulations) because the instrumental record is too short to provide a reliable estimate and may be affected by external forcing. AOGCMs may not simulate natural internal climate variability accurately, particularly on small spatial scales, and thus a residual consistency test[37] is generally used to assess the model-simulated variability on the scales that are retained in the analysis. To avoid bias, uncertainty of the estimated scaling factors is usually assessed with a second, statistically independent estimate of the covariance matrix **C** which is ordinarily obtained from an additional, independent sample of simulated unforced variation.[44]

The inversion of the covariance matrix presents problems unless very large samples of natural variability data are available. Thus, usually the dimension of the problem needs to be reduced substantially to make it treatable. The dimension used for optimal detection generally needs to be fairly small, to ensure that sufficiently many samples of long-term trends from internal variability are available from control simulations or other sources to span the covariance matrix (this is often in the order of magnitude of 5–20 degrees of freedom). Carefully thinking about the dimension of a problem is also useful because retaining dimensions that do not provide information about the signal of interest will reduce the signal-to-noise ratio.[36] The dimension reduction is often achieved by expanding the problem in the space of EOFs of the internal variability. EOFs are a convenient choice, but other choices for basis vectors can be advantageous to well represent the pattern of the climate change signal, particularly if it is not well captured by a combination of EOFs of climate variability.[38,44] A method related to optimal fingerprinting was recently suggested by Del Sole et al.,[45] who use Discriminant Analysis to identify slowly varying components in internal variability.

Thus far, we have described the so-called 'frequentist' approaches to making inferences about the contribution of external forcing to an observed change. Bayesian approaches are gaining interest in climate research because they can often be used to more formally describe the sources of uncertainty that enter into a given analysis. They also provide a means for integrating information from multiple lines of evidence. In Bayesian statistics, inferences are based on a posterior distribution that combines evidence from the observations with prior information. In principle, the latter may include information on observational uncertainty, forcing and forcing uncertainty, climate response and response uncertainty, climate model uncertainty, internal variability, and so on, thereby describing probabilistically all information that enters into the analysis. Information from climate models is an important aspect of the formulation of Bayesian approaches, but as with the standard approach, information from observations is paramount in making an

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inference about whether the observed system is being influenced by a given forcing agent. An advantage of the Bayesian approach is that detection and attribution criteria can be articulated similarly, whereas the criteria are more asymmetric in the case of standard frequentist approaches.[46,47] Inferences can be made on the basis of the posterior distribution directly[47] or by means of Bayes factors.[48] Bayes factors quantify how evidence in the observations changes the posterior odds of a pair of hypotheses relative to their prior odds.[49] Large changes, such as 10- or 100-fold increase in odds ratio, are required to claim observations contain 'strong' or 'decisive' information in support of a prior hypothesis.[49]

Most Bayesian detection and attribution studies currently available have used some variant of Bayes factors. Schnur and Hasselmann[48] described a filtering technique that optimizes the Bayes factor in a manner similar to the way in which optimal fingerprints maximize the ratio of the anthropogenic signal to natural variability noise in the conventional approach. Other studies by Min et al.[50–53] use similar approaches. In contrast, Berliner et al.[46] and Lee et al.[47] make inferences on the basis of a posterior distribution that is calculated using the scaling factor estimates from conventional optimal fingerprinting. Bayesian studies published to date have drawn conclusions consistent with those obtained via non-Bayesian approaches, so they will not be discussed in further detail in this review.

Results of Large-Scale Detection and Attribution Studies Using Climate Models

The previous section showed that fingerprint methods take advantage of using a physically based form of climate model that translates changes in radiative forcing into an estimate of the expected climatic response. The detection paradigm can use knowledge of the form of these expected responses together with estimates of internal variability to maximize their detectability in observations. In this section, models that have been used to estimate the responses are discussed, starting from very simple physical concepts to comprehensive earth system models, along with detection and attribution results based on such models.

A simple model of temperature changes would be required for deriving fingerprints of climate change, at the very minimum, to be able to account for the fact that the earth's climate responds to changes in its energy balance (i.e., to radiative forcing), and that a fast change in forcing will be translated into slower climate responses because of the ocean's thermal inertia. As an example, Held et al.[54] describe a very simple model that resolves the response of global temperature to radiative forcing, with thermal inertia separated into that due to heat uptake by the ocean's mixed layer (which occurs on timescales of years) and that due to heat transfer from the mixed layer to the deep ocean (which is a very slow process). This simple model is related conceptually to other, more complex energy balance models (EBMs).[55–57] The timescale of volcanic response in an EBM can be shown to be very similar to that derived from a tree ring-based reconstruction of Northern Hemispheric mean temperature,[58] while Held et al. show that the response of their simple EBM represents well the transient and recalcitrant response in the GFDL general circulation models.[54]

As an example of the application of a simple climate model in detection and attribution studies, we consider detection and attribution of changes resolved in palaeoclimatic reconstructions of Northern Hemispheric temperature[12] (Figure 4). The fingerprints shown in Figure 4, which in this case are obtained from a two-dimensional EBM, illustrate that the response to forcing reflects the time evolution of forcing and a time delay in the climate system's response. Fingerprints obtained with both simpler and more complex coupled climate models are very consistent with those obtained using the EBM,[12,28,58] and show that the driving factors in the detectability of past large-scale changes in temperature are relatively simple. The detection and attribution results shown in the lower panel of Figure 4 were obtained with a multiple regression approach (as discussed above) to estimate the contribution by solar, volcanic, and anthropogenic forcing to multiple reconstructions of past climate change. This study[12] showed that past climate has been affected by solar, volcanic, and anthropogenic forcing combined, that the responses to individual forcings can be separated from each other and climate variability in the reconstructed record, and that greenhouse gas increases are needed to explain recent warming in almost all analyzed records of the past millennium. Furthermore, the study showed that the influence of volcanic eruptions on the past millennium could be detected both through the short-term cooling response to volcanic eruptions and the occurrence of overall cooler multi-decade episodes that correspond to periods with multiple eruptions. In contrast, solar forcing alone could not be robustly detected, although it was detectable in some records over some time periods.

EBMs have also been used in the detection and attribution of the causes of observed changes in the instrumental record, for example in work

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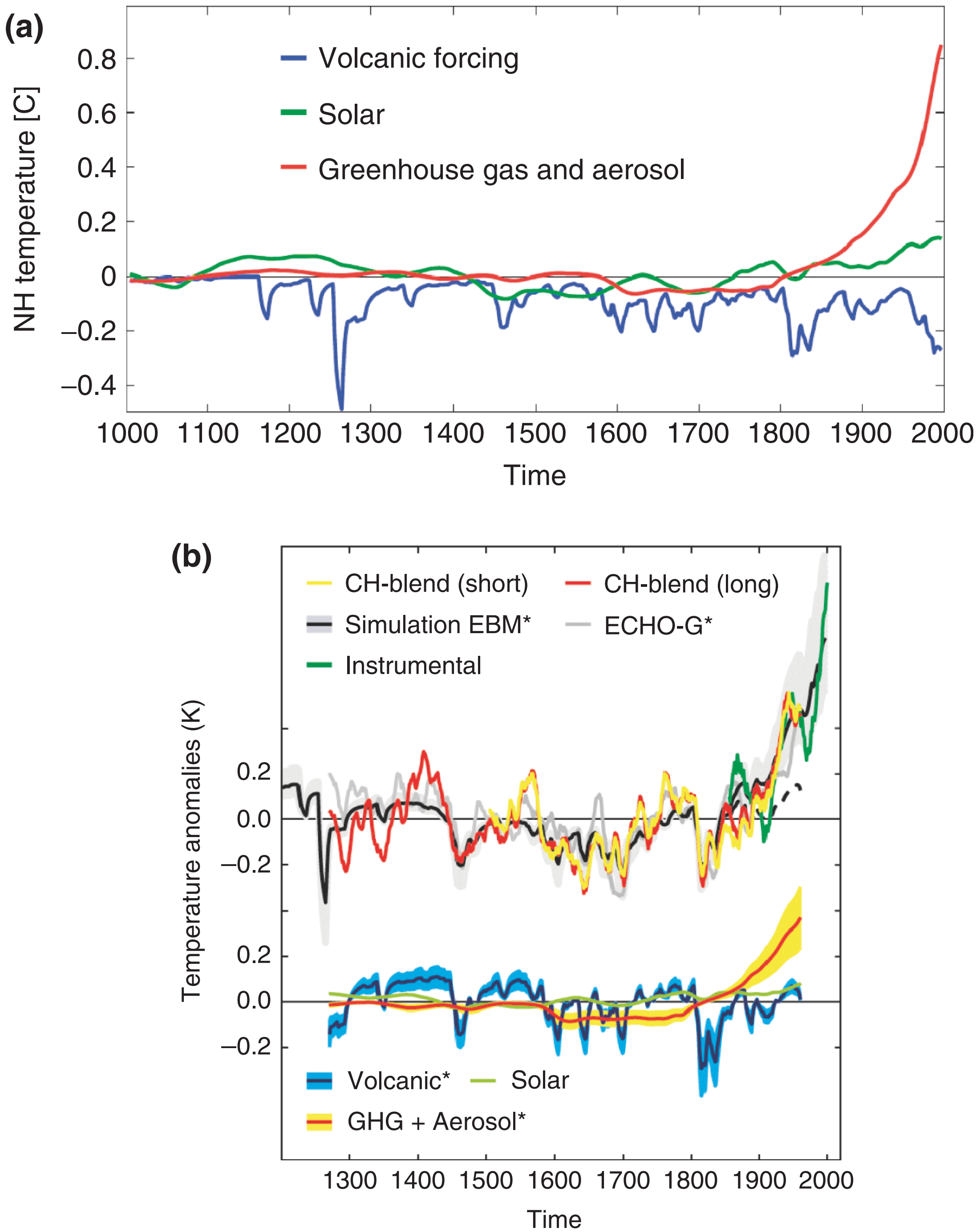

FIGURE 4 | (a) Energy balance model simulations of the response to greenhouse gas increases, moderated by aerosols in the 20th century (red), solar forcing (green), and volcanic forcing (blue) (Reprinted with permission from Ref 58. Copyright 2003). (b) Results obtained using these simulations as fingerprints for the effect of all forcings combined in a palaeoclimatic reconstruction (black, fitted to best match the reconstruction with gray shading indicating the uncertainty in the scaling factor) compared to a fit of a coupled model (grey). The lower half of the panel shows the estimated contribution by each individual forcing time series scaled to match the reconstruction in a multiple regression, with shading again indicating the uncertainty in the scaling factor and hence in the estimated contribution by individual forcings. The uncertainty in the solar signal (green) is not shown as the effect of that forcing could not be distinguished from noise ; note that similar results are obtained using a number of other reconstructions, see paper). (Reprinted with permission from Ref 12. Copyright 2007 American Meteorological Society)

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by Wigley et al.[56,57] or North et al.[59,60] or other recent approaches, some of them focusing on the role of the sun.[61–63] A range of simple models and models of intermediate complexity have also been very useful for studies determining which range of climate sensitivity yields results that are consistent with observed changes, using methods closely related to attribution techniques[65–67] (see review in Ref 64).

Nevertheless, most applications of detection and attribution methods use fingerprints and estimates of climate variability from AOGCMs or, occasionally, from atmosphere-only GCMs (AGCMs). In the early 1990s, fingerprints were usually derived from equilibrium change or future climate change simulations, as simulations of the 20th century only became available later. For example, Santer et al.[35] used fingerprints of the zonally averaged change in atmospheric temperature to discover that radiosonde-recorded atmospheric temperature changes showed an emerging trend toward the expectation from AGCMs of tropospheric warming and stratospheric cooling, consistent with expectations from radiative balance considerations. Similarly, it has been shown[38,68] that recent surface temperature trends projected well onto fingerprints of greenhouse warming derived from 21st century simulations. In a first multi-fingerprint attribution study it was also shown that the fingerprint of aerosol cooling was detectable in recent summer temperature trends, while the recent trends did not agree with expected changes from solar forcing alone.[44] While the latter article used data from simulations of the 20th century to compare the amplitude of fingerprints in observations with those presently expected based on models, it was the availability of ensembles of simulations of the 20th century that enabled Tett et al.[69] to pioneer the derivation of fingerprints of climate change from contemporaneous transient climate change simulations rather than the 21st century simulations. Fingerprints from simulations of recent climate change are much more suitable for estimating the contribution to recent observed changes from non-greenhouse gas forcings, which show a more complicated time history than simply emerging linear trends. The use of ensembles enables these more subtle fingerprints to be estimated successfully despite the presence of robust amounts of internal variability within the climate model. Fingerprints based on ensembles of AOGCM simulations of the 20th century have been applied in most recent detection and attribution studies and are assessed and reviewed in Refs 1 and 2. Only with full climate models was it possible to extend the detection of anthropogenic climate change to precipitation[70,71] (Figure 4) and sea level pressure.[19]

The key assumptions that are made when using fingerprint methods are that the response to external forcing is, apart from climate variability, a deterministic change, and that to first order, signals and noise superimpose linearly. This assumption has been tested and found valid for large-scale temperature change,[72,73] although deviations from linearity have been found for non-temperature variables such as precipitation in the tropics.[73] Although inferences about scaling factors can be made without making an assumption about how internal variability is distributed, most studies have assumed Gaussian variability. This is generally well justified because fingerprint methods are typically applied to data that have been averaged over space and/or time, ensuring via the central limit theorem[74] that the Gaussian assumption is satisfied. While the Gaussian framework is generally satisfactory for fingerprint methods, another distributional framework may be more appropriate if large-scale space/time filtering has not been performed.[75]

ROBUSTNESS OF RESULTS TO MODEL ERROR

The fact that many detection and attribution methods rely on model data makes them vulnerable to model error. This section therefore discusses how the robustness of findings can be assessed and which findings are more or less uncertain given that climate models are necessarily incomplete and that their simulations contain errors.

Robustness to Uncertainty in Fingerprints

As indicated above, most detection and attribution methods use models to estimate the expected responses to external forcing (the fingerprints) and often also use models to estimate the internal unforced variability of the climate system. Uncertainty in the fingerprints derives from a number of sources, including forcing uncertainties, so-called structural uncertainties in models, and the contamination of fingerprints by internal variability. Forcing uncertainties are discussed in *Introduction* and are particularly substantial for aerosol forcing and solar forcing.

Internal variability generated by AOGCMs or earth system models masks some of the true underlying change fingerprint in the model. Thus single simulations do not always provide good estimates of fingerprints, particularly when the signal-to-noise ratio is low. A common strategy for reducing the extent to which a fingerprint is affected by internal variability is to average across a small ensemble of simulations (typically 3–10 from a given model), each started from different initial conditions. (Note that some experiments with models having simplified oceans or reduced resolution may have orders of magnitude more ensemble members[66,76]). This averaging removes some, but not all, traces of internal variability in the fingerprint. As individual realizations can be regarded as being statistically independent, the uncertainty from internal variability in such fingerprints decreases with increasing ensemble size. As has already been discussed, uncertainty from this source can negatively bias scaling factor estimates from ordinary least squares regression, particularly in variables such as precipitation,[70] for which the response to forcing is weak relative to the background variability. Consequently, many recent studies use the TLS regression fitting technique[42] that is able to take this effect into account.

Greater sources of uncertainty in fingerprints are parameter uncertainty (uncertainty in parameters of stochastic approximations[76]) and the structure of the approximations used in climate models (so-called structural error). Here we use the term ‘structural error’ to refer to the combined effect of both types of error. Differences between models due to structural error are not always readily apparent. For example, Figure 2 shows results of 20th century simulations from the 14 models in the CMIP3 multi-model archive that included both natural and anthropogenic forcings. At the global scale, the simulated responses to anthropogenic forcing are quite similar and correspond well with observed changes (Figure 2), with the magnitude of the differences between models and individual simulations being consistent with internal variability. Differences between models are somewhat more apparent when looking at spatial patterns of change, particularly when considering projections of future change. Overall, the multi-model mean better represents late 20th century climate than the ensemble means of simulations produced with individual models.[77] Thus a strategy to further reduce fingerprint uncertainty is to construct fingerprints from multi-model means rather than from single model ensembles.[78] Confidence can be further increased by evaluating the robustness of results using ensembles of models of different quality as assessed by one or more metrics of model skill[79] (see guidance in Ref 80). Even so, uncertainty remains because the available ‘sample’ of models is finite and because this ‘sample’ cannot be considered to be representative of the population of all equally plausible representations of the climate system of a given complexity. Using model ensembles with perturbed parameters[76] helps to span more of the space of possible models, but some structural uncertainty remains.

The choice of statistical treatments of model uncertainty has had little effect on overall findings in situations when the signal-to-noise ratio is relatively robust, as with surface temperature over the past half decade. These choices range from ordinary least squares, to TLS, and to the errors-in-variables approach used by Huntingford et al.[81] Figure 3 illustrates that the estimated contribution to recent warming using a BLUE and total least square estimators is quite similar for greenhouse gas forcing when using fingerprints from individual models (red bars). In contrast, the estimated contribution from natural and other anthropogenic forcings varies more as a function of the model providing the fingerprint. Treating the available collection of models as a statistical sample allows one to account at least partially for the effects of both model differences and internal variability on the specification of fingerprints in the regression problem that is heart of detection and attribution studies.[81] The use of large multi-model ensembles and more sophisticated regression approaches has also had a great impact on our ability to detect change in non-temperature variables, such as precipitation.[70] While it is clear that the reliability of an attribution result increases when using the multi-model mean, it is presently not clear to what extent this is because of the reduction of variability in the estimated fingerprints, particularly for high-noise variables such as precipitation, and to what extent this is because of the improvement of other aspects of the estimated fingerprint such as a possible reduction in bias from sampling across multiple models.

A further source of robustness derives from the fact that detection and attribution methods do not require the models to simulate the correct amplitude of the response to forcing. In the case of temperature, while there is some uncertainty in the shape of the fingerprint, studies generally restrict themselves to the large-scale features of the response that are well simulated by most models and that are determined by large-scale geographic or climatic features (e.g., the land–sea distribution) and the characteristics of the dominant feedback processes such as snow/ice albedo feedback.[82] This implies also that uncertainty in the strength of the transient climate response should not significantly influence detection and attribution results, as the scaling factor will match the amplitude of the response to observations irrespective of the amplitude of the model fingerprint (see discussion in Ref 2). On the other hand, there is greater uncertainty in the shape of fingerprints for other variables, such as precipitation and surface pressure, both of which have response patterns that are less strongly linked to geographic features and more strongly determined

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by changes in large-scale circulation features, such as the location of the Intertropical Convergence Zone (ITCZ) and the positioning and strength of the Hadley circulation.

Confidence in results estimating the contribution by individual forcings to a recent change increases when it is clear why we can separate the influences of individual external forcings. For example, for global- and large-scale surface air temperature, a feature that helps in separating the effects of different types of forcing is their different time histories. Whereas forcing from the well-mixed greenhouse gases has increased steadily over the instrumental record in concert with increasing fossil fuel use, aerosol forcing has flattened out in recent decades due to fuel switching, economic changes, and emissions controls designed to improve air quality. In contrast, solar forcing has fluctuated both up and down slowly in time, and volcanic forcing, which is episodic, is marked by clearly identifiable events in time, with greater activity during the second half of the 20th century than during the first half of the century. Spatially, the response to forcing from well-mixed greenhouse gases is also distinct from that of other forcings, such as aerosols, although this can be affected by feedbacks. The greenhouse gas fingerprint is characterized by a slowly increasing forcing in time and a spatial response characteristic for such an increasing forcing: more warming over land than oceans, more warming in regions where the cryosphere is affected, and because of the thermal capacity of the oceans, relatively long delays in response to forcing. This contrasts with the response to aerosol forcing, which as well as having a different time history from greenhouse gases is also more prevalent in the Northern Hemisphere than in the Southern Hemisphere, with the result that aerosols have retarded warming more in the NH than in the SH (see discussion in Ref 2). These types of spatial and temporal features, which are distinct from the patterns of variation associated with natural internal modes of variability, ensure that the fingerprints are not 'multi-collinear', and therefore that they can be identified in the observations if they are present with sufficiently large amplitude.

Finally, a further point that increases confidence concerns the similarity of fingerprints for the time evolution of global mean temperature from AOGCMs and simpler models (compare Figures 2 and 4) and their similarity with results using observations only (Figure 1). This similarity across a very broad range of approaches for identifying the response to forcing in observations shows that the key features of the evolution of global temperature with time are robust to the type of model used or to not using a model at all.

However, the situation is more complex for other climate variables, for example, sea level pressure or precipitation. The time evolution of forcing should be able to help separate the response to volcanism from that to slowly increasing greenhouse gas emissions in precipitation.[71] On the other hand, it is difficult to separate the response to ozone depletion from that of greenhouse gas increases in the observed trends in the Northern and Southern Annular Modes, and while models appear to simulate a change similar to that observed in the Southern Hemisphere, they substantially underestimate the change in the Northern Hemisphere.[2,19] Similarly, climate models appear to underestimate the observed change in zonal precipitation,[70] and the aerosol impact on precipitation, including its pattern, is very uncertain.[10] This limits confidence in attribution results for non-temperature variables at present, and with it, confidence in projections of future changes.

To reduce model uncertainty, it is vital to gain a clear physical understanding of mechanisms involved in observed changes and to quantitatively confront models with observations along the chain of mechanisms involved. For example, the precipitation response to greenhouse gas forcing is influenced by a warming atmosphere, a direct radiative response in precipitation (see discussion in Ref 71), and, more uncertainly, through circulation changes. Other forcings, such as aerosols, may show characteristics that will eventually help separating their influence from that of greenhouse gases and allow for a better estimate of the greenhouse gas-driven precipitation change.

Robustness to Uncertainty in Estimates of Climate Variability

As indicated previously, climate models also play a critical role in detection and attribution studies by providing information about the natural internal variability of the climate system—chaotic variability from weather and other sources that would be present irrespective of any external influence on the system. This information can play two roles in detection and attribution; most importantly, to make inferences whether the postulated signals are present in the observations or whether an observed change can be explained by variability, and secondly in optimization that aims to maximize signal-to-noise ratios. While optimization can be important for improving the detectability of a given signal, error in the transformations that optimize the signal-to-noise ratio does not greatly affect robustness. Incorrect transformations result when the covariance structure

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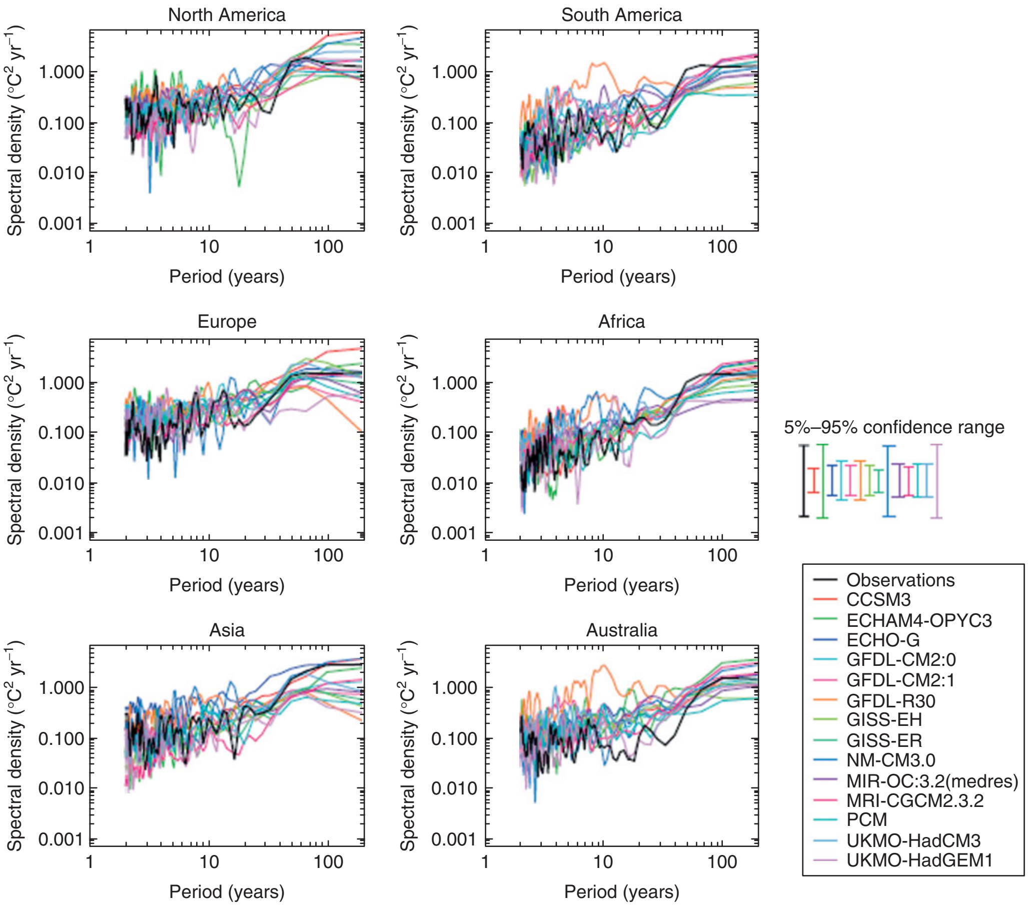

FIGURE 5 | Comparison of variability as a function of timescale for continental mean surface air temperature over the 20th century, comparing instrumental data (black) and 20th century all-forcings simulations (colors) from 14 models. The 5–95% uncertainty ranges are given by bars. Ref 2 gives details on estimation procedure. (Reprinted with permission from Ref 2. Copyright 2007 Cambridge University Press)

of the observations is incorrectly represented by the climate model and would have the effect of reducing delectability, effectively making the statistical criteria for detection and attribution more stringent.

Error in the estimate of the magnitude of internal variability, on the other hand, is a more serious issue because it directly affects estimates of the uncertainty of the scaling factors that are applied to the fingerprints—when internal variability is underestimated the uncertainty of the scaling factors is also underestimated. A number of approaches are used to ensure that detection and attribution results are robust to reasonable uncertainty in the estimates of internal variability. First, model-simulated variability is compared against observed variability. This can be done either by removing an estimate of the response to forcing from the observations, and then comparing the variability that remains against control runs,[82] or by comparing the variability of observations directly to that simulated in 20th century simulations that include both anthropogenic and natural forcings[2] (Figure 5). In both cases, it is seen that model-simulated surface temperature variability is consistent with observed variability on continental scales, although within large uncertainty ranges. In contrast, model-simulated precipitation variability may be underestimated, particularly in the tropics.[70] Second, the residuals estimated from the regression that is used in fingerprinting provide an estimate of internal variability that is based on the observations and can be compared with model-based estimates via the residual consistency test.[37] Ideally, the results of this test should be robust to reasonable changes in the analysis, for example in truncation level (see above). As a third step, model-simulated variability is often inflated by an arbitrary factor of two or more so as to assess the robustness of detection and attribution findings under the conservative assumption that models have underestimated internal variability. Global-scale detection and attribution results for temperature are typically found to be robust even with very substantial variance inflation factors.[2] For precipitation, key results are robust to inflating variance by a factor of two,[70] and uncertainty in precipitation variability is further discussed below. And finally, the variability in reconstructions of climate of the last millennium that is not explained by external influences (Figure 4) can be used as a comparison against climate model unforced variability. On interdecadal timescales, this residual variability is similar to or smaller than that of several AOGCMs.[12,58] Thus, the assessment that greenhouse gas increases has very likely influenced recent temperatures is based on robustly assessed temperature variability, while detected signals in non-temperature variables are more affected by uncertainty in model variability.

TOWARD DETECTION AND ATTRIBUTION OF REGIONAL CHANGES AND IMPACT RELEVANT CLIMATE VARIABLES

Increasingly, attention has been focused on regional questions and changes in impact relevant variables, such as regional patterns of temperature change[33,83–86] (see also Ref 1), precipitation,[70,87] the hydrological cycle,[88,89] and temperature and precipitation extremes or impacts (Box 1).[90–93] Also, regional models or high-resolution models are becoming important to derive fingerprints,[94] and the use of earth system models will enable fingerprints to extend to variables such as carbon cycle feedbacks[95] or vegetation, or derive fingerprints for greenhouse gas concentrations from the combination of emissions and feedbacks.

As has been discussed above, uncertainties in both forcing and response are of significantly greater concern for regional detection studies[2] and for non-temperature variability such as precipitation.[70,71,87] Regional signal separation is limited by lower signal-to-noise ratios that arise because there is less opportunity to spatially filter out the effects of low-frequency internal variability. Also, there is often a lack of sufficient signal detail in space and time to permit signals from different sources to be distinguished. It may be possible to overcome the former problem through more sophisticated temporal filtering than used previously or by borrowing information from adjacent regions. For example, Christidis et al.[96] make inferences about the contributions from anthropogenic and natural forcings to regional temperature change based on a global-scale detection and attribution analysis. A related approach that may be useful in instances when the detection and attribution study involves a spatial index, such as sea-ice extent, is to add structure to the signal by considering the evolution of the annual cycle over time.[97] The increasing resolution of global and regional climate models, together with more detailed specification of regionally important forcings, such as land-use change and the inclusion of short-lived forcings including absorptive as well as reflective aerosols, will help to resolve the latter problem. Additionally, dynamical and statistical downscaling may be an option for developing impact relevant signals with more specific spatial structure.[88]

Obtaining credible estimates of internal variability can be more challenging in cases, such as precipitation,[70,87,93] where models are suspected of undersimulating internal variability due to differences in the scales that are represented by models and observations (Figure 6(b)). Precipitation observations from rain gauges represent point values and display temporal and spatial variations in intensity that are generally not simulated by global climate models. Aggregation of available gauge data within grid boxes can ameliorate this 'scale problem' somewhat[98,99] but does not seem to completely resolve the issue. Additionally, transformations of precipitation into dimensionless units that are applied separately to observations and models, such as the probability integral transform that maps precipitation onto a (0,1) scale, may be useful.[93] Restricting the analysis to periods with greater data coverage may also be helpful in constructing more robust estimates of internal variability because sparse coverage reduces the ability to filter short space–timescale noise from observations and model output alike. Available detection and attribution studies on precipitation[70,87,93,100–102] have gone to great lengths to assure the quality of the observational data and to examine the robustness of detection results to variations in the construction of fingerprints and model-simulated internal variability, including by inflating the model-simulated variability in detection and attribution studies.

BOX 1

USING MODELS TO ATTRIBUTE IMPACTS OF CLIMATE CHANGE TO FORCING

The information obtained by confronting models with observations in detection and attribution studies tells us much about the reliability of models and can be used to constrain projections of future change and to quantify their uncertainty.[103] Detection and attribution techniques can also be used to understand changes in impacts. The challenges in attributing impacts to changes in external drivers are often substantial. Data for variations of species distribution, human health, migration patterns,

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flowering dates, and similar impacts are often limited, and their spatial and temporal sampling is not homogeneous (see discussion in Ref 104). Moreover, these variables are impacted not only by climate, but also by other, often confounding, factors that are not related to climate (see guidance in Ref 105). Despite these challenges, it is important to assess the extent to which an observed impact is due to greenhouse gas increases or due to other climatic or non-climatic factors. As greenhouse gases are expected to continue accumulating in the atmosphere, greenhouse gas-driven changes will persist and intensify, while changes due to many other factors may be more reversible. A variety of methods can be used to attribute impacts to climate change, and only in rare cases can one single model be used for modeling the fingerprint for the response in the impact under consideration to different forcings and climate variability directly (an example might be large-scale vegetation change in earth system models). Often, data from climate models are used to obtain information on changes in the physical climate, and then an additional modeling step or statistical link is employed to estimate the response of an impact variable to a changing climate (for more information, see Ref 105). For example, Gillett et al.[106] used a simple statistical model to post-process results of climate model simulations driven with anthropogenic forcing into estimates of the forced response in area burnt in forest fires in Western Canada. They also post-processed a control simulation so as to obtain an estimate of the internal variability in area burnt on multi-decadal timescales. Even though multiple modeling steps were used, the approach is very similar to usual detection and attribution approaches: The observed change is directly compared against changes in area burnt resulting from climate variability and changes resulting from external drivers. This is termed 'single step' attribution[105] because a single attribution step is performed. Sometimes, it is more feasible to first estimate the change in a climate variable due to external forcing and in a second ('multi-') attribution step, determine the change in a variable tightly related to climate, or for a system for which climatic drivers have been isolated. In the latter case, it may be more difficult to estimate the magnitude of the contribution to an impact by, for example, greenhouse gas forcing. A further difficulty is that the response, for example in a species, can be driven by climate on small spatial scales or even individual events. Attributing individual climate events to causes is challenging, is only possible probabilistically (in the sense that greenhouse gas forcing, for example, may have influenced the probability of events[107]), if at all, and has only been achieved in rare instances to date.[108,109] Sometimes, spatial aggregation of multiple lines of evidence can help,[104] although the information is often inhomogeneous and derived from multiple studies using different levels of complexity and completeness. In both single- and multistep approaches, models of some type, including statistical models, are needed to link an impact to a changing climate.

CONCLUSION

Climate change detection and attribution is first, and foremost, about understanding observed changes. However, detection and attribution requires a model of why climate may be changing to be able to draw conclusions from observations. Models used in the interpretation of observations can range from simple conceptual 'models' to climate models of intermediate complexity, and ultimately to coupled atmosphere–ocean general circulation models and earth system models.

Conclusions on observed large-scale temperature changes are robust to the choice of model that is used to express how temperature is expected to have changed in response to forcing. Simple conceptual models, for example, based on a separation between signal and variability on timescale, allow the identification of changes in observations that are qualitatively consistent with expectations from more physically based models. Results using the most complete and complex climate models provide results that are consistent with those using simpler models, but provide much more information on expected signals. This additional information improves the signal-to-noise ratio of individual climate change signals and improves the ability to distinguish between the components of observed climate change corresponding to the responses to different external forcings.

The different methods used in detection and attribution research differ in their robustness to assumptions and to model error. Simple methods that compare changes in response to one hypothesized cause to that due to other hypothesized causes are sensitive to errors in the magnitude of climate change, and with that, to errors in transient climate response and in the magnitude of external forcings.

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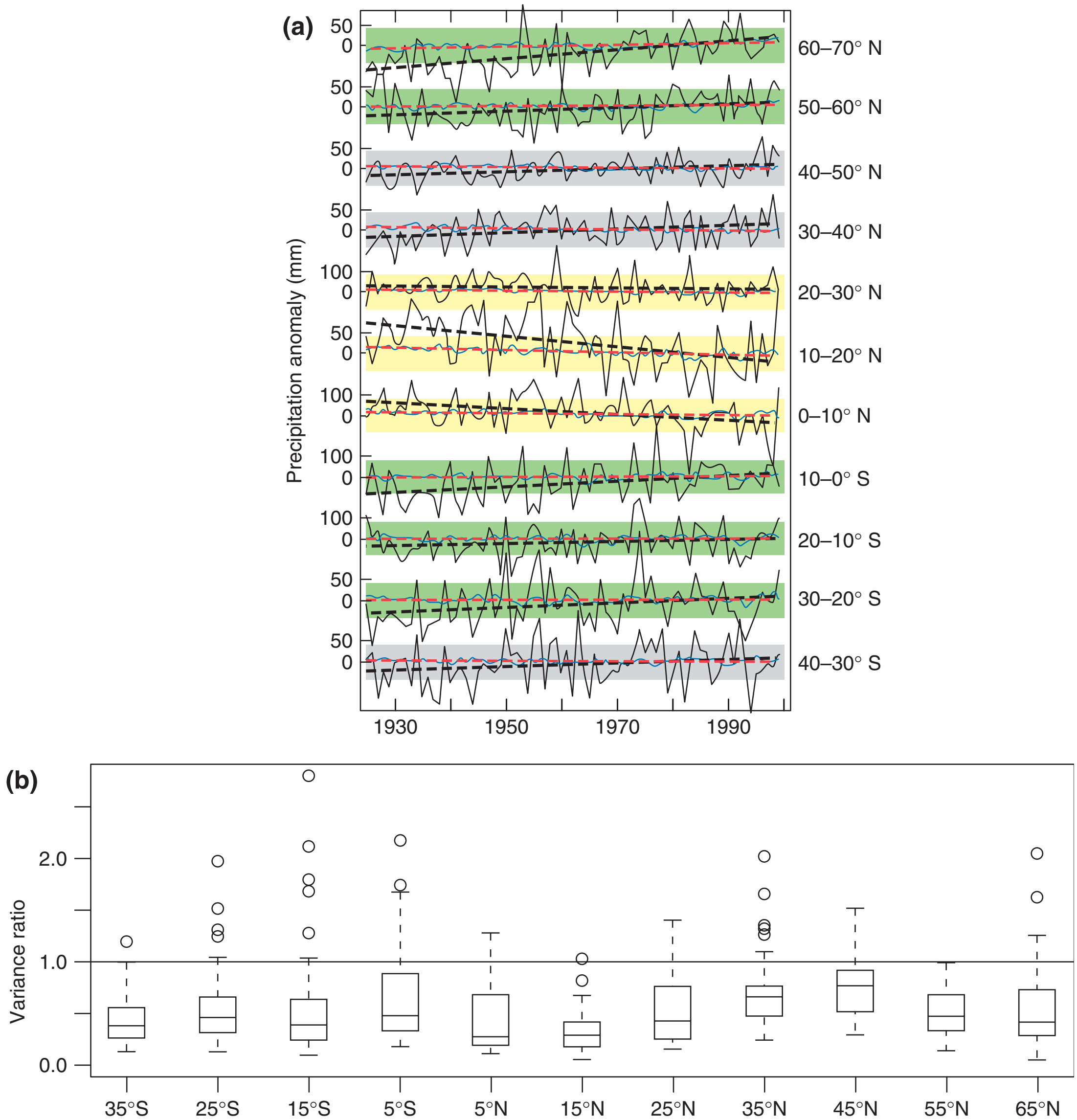

FIGURE 6 | (a) Comparison of precipitation in zonal latitude bands between a multi-model mean (blue time series, trend shown by red dashes) and observations (black, trend shown by black dashes), overlay colors indicate bands where both model and observations show increases (green), decreases (yellow), or neutral/disagreeing sign of change (gray), and (b) zonal pattern of variance ratio between climate models and observations. The figure shows box and whisker plots of the ratio of 5-year 10° zonal mean precipitation variances between all-forcing simulations and that estimated from station observations. The upper and lower ends of each box are drawn at the 75th and 25th quartiles, and the bar through each box is drawn at the median. The two bars indicate the range that would cover approximately 90% of variance ratios if the upper or lower halves of the variance ratio distribution were roughly Gaussian in shape. Individual points beyond the horizontal bars indicate outliers. (Reprinted with permission from Ref 70. Copyright 2007 Nature Publishing Group)

Pattern correlation methods and regression methods that estimate the magnitude of fingerprints from observations are insensitive to the magnitude of changes simulated in response to forcing but are sensitive to uncertainties in the pattern of response or forcing. Regression methods have advantages over pattern correlation methods in that signal-to-noise ratios can be optimized, multiple signals can be considered simultaneously in a straightforward manner, and signal uncertainty from internal variability, and to some extent structural error, can be taken into account. To the extent that existing estimates of forcing cover the true forcing, forcing uncertainty can be assessed by using model simulations driven with different forcing estimates, and the effect of error between models can be assessed by using multi-model fingerprints and by using large perturbed physics ensembles. However, the effect of errors common to all models cannot presently be assessed. Similarly, the effect of errors in observations has been estimated, but can only be assessed to the extent that the space-time characteristics of uncertainty are known. Here, arguments of physical consistency of observed changes between variables and with assumptions are helpful and improve the reliability of results. Further studies of multiple climate models with perturbed parameters (such as in Ref 76) will help to better understand this remaining model uncertainty, and emulators[110] may help to more fully explore model uncertainty.

The attribution results for large-scale temperature changes are supported by a large number of different lines of evidence and are robust to using very simple to fully complex models. They are also robust to using different methods and to using different assumptions and even approaches that avoid direct use of models altogether. They are also physically consistent with detection and attribution results from other climate variables, including, for example, tropopause height, vertical temperature of the atmosphere, atmospheric humidity, and to some extent, precipitation changes (see discussion in Refs 2 and 71). The process understanding of the way the different forcings work and the ability of climate models to simulate key characteristics of observed changes increase confidence in detection and attribution results on those large and temperature-driven scales. For improved prediction of future climate change and connection of climate change impacts to external drivers,[111] however, smaller scale changes in variables other than temperature are required, which will continue to be challenging. For example, reliable prediction of precipitation changes is vital for impacts of climate change and for discussion of geoengineering options, and present models may underestimate the magnitude of the response.

Detection and attribution results not only use climate model results, but ultimately, these results are a very powerful test of climate model simulations. Where the regression residual is larger than expected due to noise, this raises important questions about the appropriateness of the statistical assumption or the model fingerprints and variability. Situations where the simulated change in response to external forcing is detected in observations, but with an amplitude that is significantly (even if accounting for observational uncertainty) different from that estimated from models indicate that the model or its external drivers are in error. Thus, detection and attribution results not only robustly benefit from climate model simulations, they also evaluate them.

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