Overview

Detection and attribution of climate change: a regional perspective

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The Intergovernmental Panel on Climate Change fourth assessment report, published in 2007 came to a more confident assessment of the causes of global temperature change than previous reports and concluded that 'it is likely that there has been significant anthropogenic warming over the past 50 years averaged over each continent except Antarctica'. Since then, warming over Antarctica has also been attributed to human influence, and further evidence has accumulated attributing a much wider range of climate changes to human activities. Such changes are broadly consistent with theoretical understanding, and climate model simulations, of how the planet is expected to respond. This paper reviews this evidence from a regional perspective to reflect a growing interest in understanding the regional effects of climate change, which can differ markedly across the globe. We set out the methodological basis for detection and attribution and discuss the spatial scales on which it is possible to make robust attribution statements. We review the evidence showing significant human-induced changes in regional temperatures, and for the effects of external forcings on changes in the hydrological cycle, the cryosphere, circulation changes, oceanic changes, and changes in extremes. We then discuss future challenges for the science of attribution. To better assess the pace of change, and to understand more about the regional changes to which societies need to adapt, we will need to refine our understanding of the effects of external forcing and internal variability. © 2010 John Wiley & Sons, Ltd. *WIREs Clim Change*

There is a wealth of observational evidence that climate is changing and which led the Intergovernmental Panel on Climate Change fourth assessment report (IPCC AR4) to conclude that warming of the climate system is unequivocal.[1] Such changes include global mean temperature, the extent of Arctic sea ice, and global average sea level, all of whose values averaged over the most recent decade are substantially different than they were half a century or more earlier. While the observational record leaves little room for doubt that the earth is warming, the evidence does not by itself tell us what caused those changes. We could be experiencing natural fluctuations of climate operating on multidecadal timescales. Alternatively, drivers of climate change, such as volcanic eruptions or human-induced emissions of greenhouse gases, could be forcing sustained changes in climate. Detection and attribution seeks to determine whether climate is changing significantly and if so what has caused such changes.

Such an understanding has many potential applications. First, it makes sense to reduce greenhouse gas emissions if they are contributing significantly to climate change. Second, attribution studies are needed to understand the current risks of extreme weather.

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DOI: 10.1002/wcc.34

Under a nonstationary climate, we can no longer assume that the climate is, as has been traditionally assumed, the statistics of the weather over a fixed 30-year period: what were previously rare events could be already much more common. Instead, models are needed to characterize the current climate, which can be different from that of previous or succeeding years. Third, by comparing observations with models in a rigorous quantitative way, attribution can improve confidence in model predictions and point out areas where models are deficient and need improving.

There have been many advances made since the AR4 that refine our understanding of human-induced climate changes, and the objective of this paper is to review these advances. We have a regional focus because human influences can lead to very different climatic changes in different parts of the world. In addition, natural climate variability can be important at regional scales. Successful adaptation will necessitate increased understanding of such regional differences.

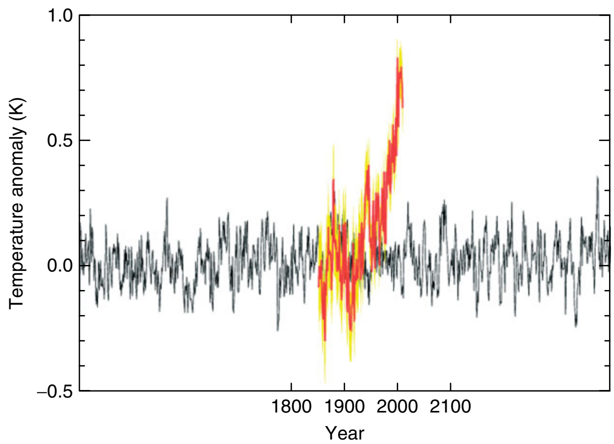

FIGURE 1 | Observed global mean temperature changes from 1850 to 2008 (in red) from HadCRUT3v with uncertainties (yellow band as derived by Brohan et al.[7] and expressed as anomalies relative to the mean temperature over the 1861–1899 period) overlain on a 1000 year segment of global mean temperatures from control simulations from the HadGEM1 model (black line).

WHAT DO WE MEAN BY DETECTION AND ATTRIBUTION?

Detection is the process of demonstrating that climate has changed in some defined statistical sense. Thus detection seeks to determine whether observed data indicate that climate is changing or are simply consistent with possible fluctuations from natural internal variability of the ocean atmosphere system. Figure 1 shows an example of a detection analysis. A 'control' simulation of a coupled ocean–atmosphere climate model over many centuries, with no changes in the external drivers of climate such as increases in greenhouse gas concentrations or in solar output, does not exhibit the sustained rise in temperatures seen in the observational data. A statistical test shows that the 50-year global warming trend observed from 1959 to 2008 is detected at the 5% significance level, as there is a less than 5% likelihood of such a large trend due to internal variability alone, according to the control simulation.

Multicentury long estimates of natural internal variability from models are needed because equivalent estimates cannot be obtained from observational data, in part because the instrumental record is too short to yield the reliable estimates of internal variability that are required for detection and attribution, and in part because the observational record is not free from the effects of external influences. However, observational data are used to evaluate the internal variability produced by climate models over decadal and multi-decadal timescales (see Ref 2 for further discussion).

With 1998 having a strong El Nino, and consequently a very warm year globally, trends since 1998 have shown little warming or cooling, a fact which has been used by some to claim that global warming has stopped or slowed down. However, as demonstrated in papers by Easterling and Wehner[3] and by Knight et al.,[4] decade long trends with little warming or cooling are to be expected under a sustained long-term warming trend, as a result of multidecadal scale internal variability. In addition, Zorita et al.[5] have shown that the observed recent clustering of warm record-breaking global temperatures is very unlikely to have occurred by chance in a stationary climate. Further refinement of our understanding of the causes of decadal variability would benefit from tracking the changes of energy within the climate system[6] and better understanding of the role of natural and human-induced external drivers of climate, including, for example, the effects of changing solar activity.

Attribution is the process of establishing the most likely causes for a detected change with some level of confidence. We seek to determine which external forcing factors have significantly affected the climate, where external forcing factors are agents outside the climate system that cause it to change by altering the radiative balance or other properties of the climate. Examples of anthropogenic external forcing factors include increases in well-mixed greenhouse gases and changes in sulfate aerosols. Aerosols affect clouds and can make them more reflective and scatter more incoming solar radiation to space, and incoming solar radiation can also be affected by natural forcing

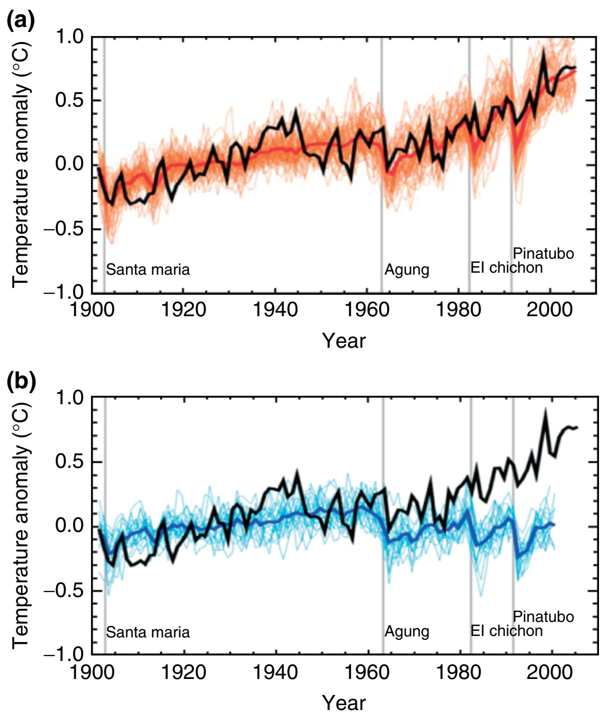

FIGURE 2 | Global mean surface temperature anomalies relative to the period 1901–1950, as observed (black line) and as obtained from climate model simulations with (a) both anthropogenic and natural forcings (red lines) and (b) natural forcings only (blue lines). Vertical gray lines indicate the timings of major volcanic eruptions. The thick red and blue curves show the multiensemble means and the thin lighter curves show individual simulations. (Reproduced from IPCC AR4 WGI report; Figure TS.23).

factors which include changes in output from the sun and changes in stratospheric aerosols from volcanic eruptions. External forcings such as increases in carbon dioxide and changes in land cover can force the climate by changing evaporation from the Earth's land surface and transpiration of plants. Figure 2 shows that observed global mean temperature changes are consistent with the spread of those climate model simulations analyzed in the IPCC AR4 report that include anthropogenic and natural forcings but not with the spread of alternative climate model simulations that exclude anthropogenic forcings.[1]

The standard approach to attribution is to use a climate model to determine the expected response to a particular forcing. Such a response, often denoted the fingerprint of the expected change, results from many processes acting in the atmosphere and ocean and is affected by feedbacks, such as, for example, decreasing albedo from melting snow and ice. Once the fingerprints have been derived, an analysis is carried out to determine if there is a significant manifestation of these fingerprints in the observations.

The simplest technique is to compare observed changes in aspects of the fingerprint with model simulations with and without anthropogenic forcings, as illustrated in Figure 2. Direct comparisons of this sort can be used to produce likelihood measures which can be evaluated in a Bayesian framework to decide on the most probable of competing explanations.[8,9] Such a consistency analysis satisfies the standard definition of detection and attribution but it does not quantify the relative contributions of anthropogenic and natural factors. While the scales on which the signal emerges above the noise may limit the detectability of regional signals, these scales are likely to reduce as the climate signal strengthens[10] and indeed observed changes may already be detectable at climate model grid box scales (~500 km) in many regions.[11] However, key problems for regional attribution are the extent to which models are able to reliably capture the effects of external forcings and of internal variability at these small scales, and the extent to which the responses to different forcings can be individually distinguished in observations at these scales. Misattribution could result if consistency between observations and models is found as a result of compensating errors arising fortuitously from missing processes in models, such as the effects of locally important forcings (e.g., the effects of black carbon, missing from many climate models, in darkening the snow surface and accelerating Arctic warming[12] or poor simulations of regional circulations.

An advance on simple measures of consistency is to compare observations with the responses to a range of possible forcing factors in a linear regression approach. Observed changes, y, are expressed as a linear sum of m model fingerprints, x_i, where u_0, represents internally generated variability:

$$y = \sum_{i=1}^{m} (x_i - u_i)\beta_i + u_0. \qquad (1)$$

The assumption of linearity is found to hold for some combinations of forced changes, particularly the direct effects of sulfate aerosols and greenhouses,[13–15] although there is evidence that additivity does not hold so well for some other combinations, including greenhouse gases in combination with the indirect effects of aerosols[16] and greenhouse gases with solar forcing[17]; The fingerprints, x_i, are estimated from the average of a finite number of simulations with identical forcings but different initial conditions (typically 3 or 4 for most analyses), and are contaminated by internal variability (which reduces as more ensemble members are averaged); this noise is represented by $u_{i..}$ Long model control simulations, such as that shown in

Figure 1 in which external forcings are held constant, provide estimates of internal variability via the covariance matrix of u_0 and u_i. In optimal detection, the observations and fingerprints are normalized by the climate's internal variability (as estimated from the long control simulation). This normalization is standard in generalized linear regression and is used to improve the signal-to-noise ratio (see Ref 18 for more detailed discussion). A standard consistency test[19] is used to assess whether the residual of the regression is consistent with the model-derived internal variability, as expected if the scaled fingerprints are able to capture the observed forced changes. Further details on the methodology and examples of applications are provided by Ref 2 and references therein.

The scaling factor for each model experiment, β_i, determines whether that forcing factor has been detected and measures the level of consistency between the model fingerprint and the observations. If an estimated scaling factor is positive and its 5–95% uncertainty range is inconsistent with zero then the signal is detected at the 5% significance level (meaning there is a 5% risk that the null hypothesis of no significant influence of that forcing is true but is rejected). Values consistent with unity and with a small uncertainty range imply good agreement between the model and the observations. Values inconsistent with unity imply a discrepancy between modeled and observed changes which could be a result of problems with the observational records or missing processes in models.

Scaling factors from analyses using different climate models applied to large-scale space time patterns of near-surface temperature over the 20th century are shown in Figure 3(a) where the observations have been regressed against components due to three factors: greenhouse gases, other anthropogenic forcings (dominated by the effects of tropospheric sulfate aerosols) and natural factors (volcanoes and solar). In every case, the estimated scaling factor for greenhouse gases (red bars in Figure 3(a)) has a narrow 5–95% uncertainty range that excludes zero, indicating that their influence has been robustly detected. This is also the case for other anthropogenic factors (green bars), although it appears that the response to non-greenhouse gas anthropogenic factors is underestimated in the Parallel Climate Model (PCM). In contrast, the influence of natural factors (blue bars) is not detected in every case. Where observed changes are not consistent with internal drivers or natural climate drivers alone and the effects of anthropogenic forcings have been detected in a multivariate regression, it is appropriate to conclude that significant observed changes are attributable to human influence. For global surface temperatures, there is a very clear attribution to human influence that is robust across a range of models and analyses.

Figure 3(b) shows an example of how attribution analyses are able to quantify the contributions of different forcings, here expressed as trends over the 20th century. Figure 3(b) shows that there is a greater degree of consistency across the models for trends attributable to greenhouse gases than for the trends attributable to other factors. In fact, as discussed in detail by Stott et al.,[21] the observed patterns in space and time of surface temperatures over the last century provide a valuable observational constraint on the likely range of warming attributable to greenhouse gases. As a result the model with the lowest sensitivity of those considered in Figure 3 (the PCM model) has a 5–95% range of scaling factors greater than one, indicating evidence that the model's response should be scaled up significantly to be consistent with that observed.

Discussion to this point has focused on analyses using fingerprints derived from individual models (i.e., the first four columns in Figure 3) which assume that the model predicted pattern of response to a particular forcing is correct, subject to a uniform scaling. A further enhancement is to include several climate models in a single analysis thereby making it possible to estimate the uncertainty in response patterns,[22,23] and a more comprehensive estimate of attributable changes. Such an analysis (from Ref 23) is shown by the set of bars on the right hand side of Figure 3 (denoted by EIV).

Understanding of the past provides increased confidence in predictions of likely changes in future. In particular, there is a close relationship between past and future greenhouse gas warming,[24,25] and uncertainties in future warming can be derived based on attribution of past warming.[21,24,25] These observationally constrained analyses, such as those shown in Figure 3, indicate that it is very likely that aerosol cooling is suppressing a major portion of current greenhouse warming (see Ref 26 as illustrated by the fact that all the green bars in Figure 3(b) are below the x axis) as suggested by pure modeling studies.[27] As a result, additional warming is implied if aerosol pollution is removed from the atmosphere in future.

TEMPERATURE

We take a regional perspective in this review to reflect the growing need for attribution studies to go beyond globally averaged quantities and consider how climate change varies across the globe. We divide our review of temperature attribution into a

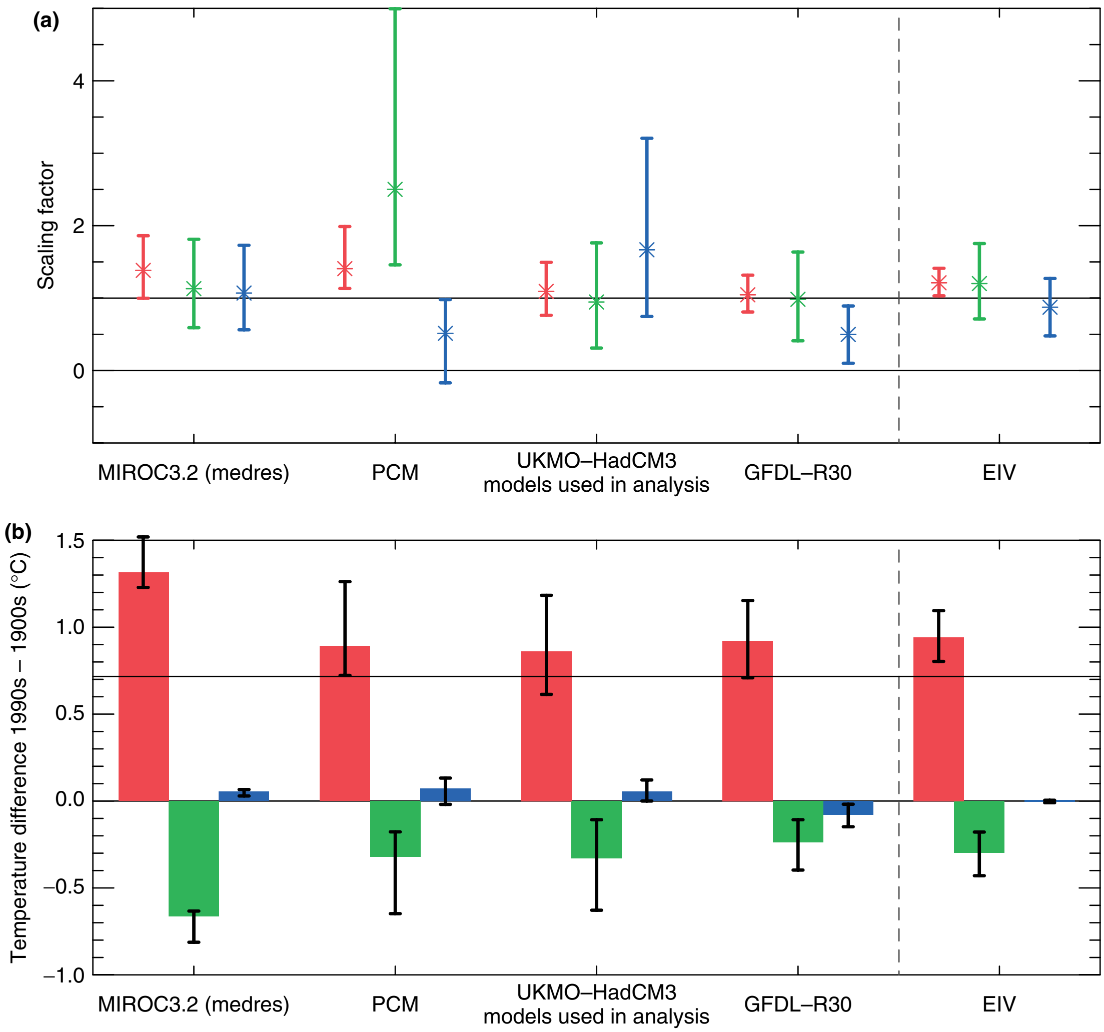

FIGURE 3 | Estimated contribution from greenhouse gas (red), other anthropogenic (green) and natural (blue) components to observed global surface temperature changes. (a) 5–95% uncertainty limits on scaling factors based on an analysis over the 20th century, (b) the estimated contributions of forced changes to temperature changes over the 20th century expressed as the difference between 1990–1999 mean temperature and 1900–1909 mean temperature. The horizontal black line shows the observed temperature changes from HadCRUT2v.[20] Five different analyses are shown using different models which are explained in more detail in the text. Adapted from Hegerl et al.[2]

subsection on continental and subcontinental scales, where by subcontinental scales we mean a subdivision of continents into a small number of regions, and a subsection on smaller scales, going down to the scales of climate model grid boxes or of order 500 km.

Continental to Subcontinental Scale

The first systematic investigation of continental scales to use the optimal detection regression approach described above was by Stott.[28] This study found a detectable change over the 20th century in decadal mean temperatures over each of the six populated continental areas (Europe, North America, South America, Asia, Australia, and Africa), and furthermore found that these changes could only be reproduced with the inclusion of anthropogenic greenhouse gas emissions. These conclusions for the northern continents were supported by the studies of Karoly et al.[29] and Zwiers and Zhang[30] which focused on the continents of North America, Europe, and Asia. More recently, Gillett et al.[31] used a similar approach to examine surface temperatures over Antarctica and detected an anthropogenically forced warming over the past 50 years. Thus, anthropogenically forced temperature changes have now been detected on each of the seven continents.

Recent work has extended these results further, to smaller scales and seasonal averages. Min and Hense[32] used a Bayesian decision approach which classified seasonal temperature changes over the six populated continents according to proposed causes. Not only was the decision in favor of requiring anthopogenic forcing for most continent-season cases, but the decisions also proved robust to the degree of prior expectation of no detectable change.

Jones et al.[33] examined summer (June–August) mean temperatures over the past century over a set of standard subcontinental regions of the Northern Hemisphere. These subcontinental regions divide each of the six continental region into a small number (between two and six) subregions chosen to represent different climate regimes.[34] When signals were regressed individually against the observations, an anthropogenic signal was detected in each of 14 regions except for 1, central North America, although the results were more uncertain when anthropogenic and natural signals were considered together. Zhang et al.[35] examined the detectability of the seasonal signal of anthropogenic forcing as a function of spatial scale in the Northern Hemisphere. Consistent with the Jones et al.[33] results, they found robustly attributable signals down to the continental scale, with the effects of both anthropogenic greenhouse gases and aerosols being detected separately. Gillett et al.[36] detect a human influence on summer season warming in Canada and demonstrate a statistical link with area burned in forest fires.

An example of such an analysis for Eastern North America carried out with the PCM and HadCM3 climate models is shown in Figure 4. This illustration shows that the effects of greenhouse gases are clearly detected in this region (the red bars in Figure 4(b) are above the x axis). The regression procedure scales the models' responses to the different forcings to produce a better agreement with the observations.

Smaller Scales

These regional studies described so far are approaching the scale of administrative divisions. However, difficulties remain in attributing observed temperatures changes at regional scales. Regional temperature and precipitation are affected by low-frequency variations in atmospheric circulation, such as associated with the North Atlantic Oscillation (NAM) or the Southern Annular Mode (SAM).[37] Wu and Karoly[11] considered observed warming trends over the period 1951–2000 in individual regions of order 500 km scale. They found significant warming trends, outside the range of natural variability, in more than 50% of the individual regions, even allowing for the influence of changes in atmospheric circulation. Bhend and von Storch[38] and Bonfils et al.[39] have examined smaller spatial scales by using multiple modeling methods to create higher resolution datasets. While these studies considered smaller scales, neither considered a range of factors, such as land use change, irrigation or reservoir construction, which could cause climatic responses with small-scale spatial structure. Additional forcing factors, including aerosols, are also likely to be more important at regional scales. Relevant model simulations considering the different forcing factors separately are often not available, so the attribution to different forcings is limited to a consistency analysis rather than a full attribution analysis in which all plausible forcing factors are considered. For example, increases in irrigation in California have been important for regional temperature trends,[40] while land cover change can be important for regional temperature changes.[41,42]

As an example of a regional consistency attribution study, Karoly and Stott[43] considered observed central England temperatures and simulated temperatures from a single climate model grid cell. They showed that model-simulated variability of central England temperature agreed well with that observed at interannual, decadal, and 50-year timescales. They concluded that the observed warming trends over the last 50 years are very unlikely to be due to natural internal variability, cannot be explained by the response to changes in natural external forcing, and are consistent with the response to changes in anthropogenic forcing, increases in greenhouse gases and aerosols. This is an example of a consistency study, as only a limited number of possible forcing factors were considered and the contributions of the different factors to the observed warming were not estimated. Dean and Stott[44] carried out a similar consistency analysis for New Zealand but in addition took account of the most important mode of regional climate variability that has caused a trend to more southerly flows in recent decades and hence a reduction of New Zealand warming. On removal of the influence of this circulation variability, they found that recent trends in the residual temperature record cannot be explained by natural climate variations but are consistent with the combined climate response to anthropogenic greenhouse gas emissions, ozone depletion and sulfate aerosols, demonstrating a significant human influence on New Zealand warming. Variability at regional scales can mask or accelerate human-induced warming and a full understanding of such effects requires climate models that can adequately capture such variability.

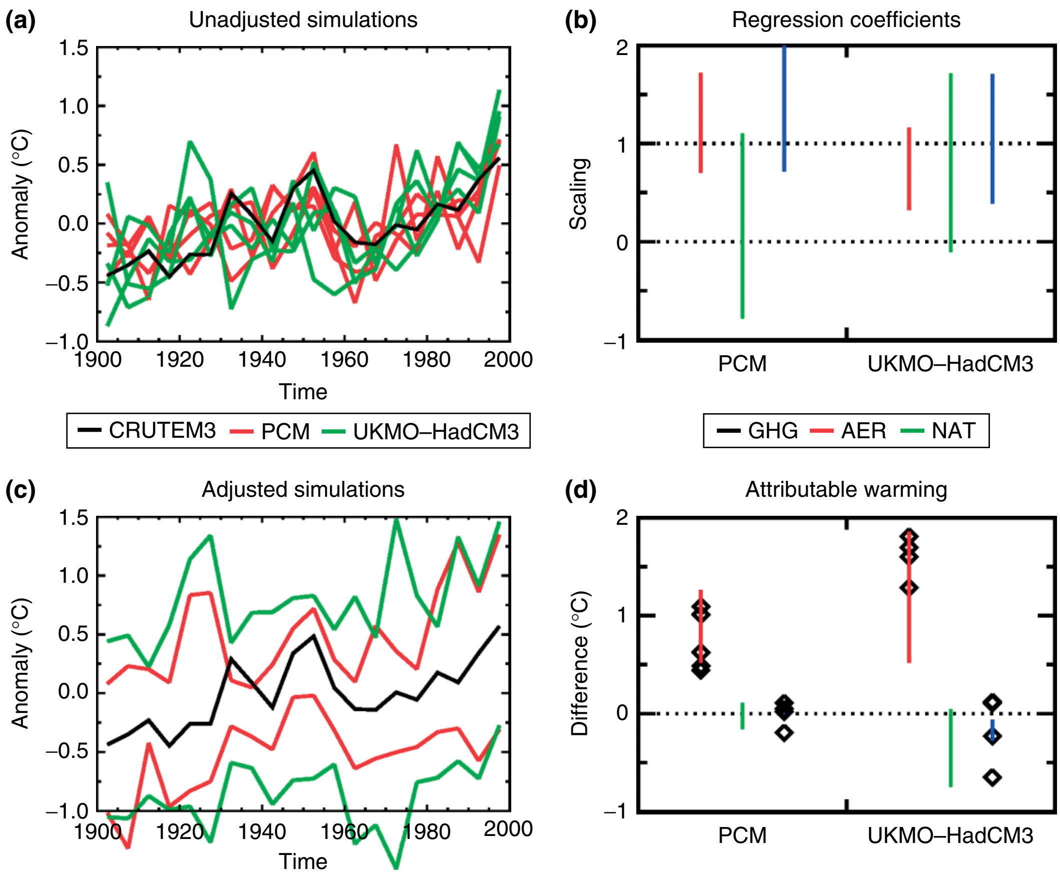

FIGURE 4 | Regression analysis of 5 year, area mean temperature variations over Eastern North America during the 1900–1999 period. (a) Data from CRUTEM3 observations[7] (black) and from simulations of two climate models including both natural and anthropogenic forcings (red and green). (b) 5–95% confidence intervals on scaling coefficients for the responses to various forcings in each climate model using the regression formula in Eq. (1). Simulations with historical greenhouse gas forcing only, historical natural forcings only, and both natural and anthropogenic forcings were input into the analysis. Scalings are shown for the responses to greenhouse gas forcing (red), sulfate aerosol and other anthropogenic forcing (green), and natural forcing (blue). (c) The resulting 5–95th percentile ranges on possible 5-year average temperatures for the two climate models (red and green), compared to observations (black). (d) The warming between the 1900–1909 and 1990–1999 periods attributable to each of the external forcings. Diamonds show estimates from individual simulations (black). Lines show the estimated 5–95% confidence interval estimated using the linear regression analysis. Note that the larger warming of the PCM model over the UKMO-HadCM3 model visible in (a) was adjusted through the different greenhouse gas forcing scalings in (b), producing better agreement between the models in (c) and (d).

With growing concerns about regional impacts of climate change in natural systems, attribution of climate change to anthropogenic forcing at regional scales is becoming more important. However, as was also discussed by Hegerl et al.,[2] attribution at regional scales is limited at present by the relatively lower signal-to-noise ratios, the difficulties of separately attributing the effects of the wider range of possible forcing factors at these scales, and limitations of models in capturing some characteristics of regional climate variability.

One issue to be addressed is how to combine global scale and regional scale information in the same analysis. Rather than analyze each separate region in isolation, Christidis et al.[23] calculated distributions of regional trends using constraints from a global optimal detection analysis and multiple climate models. Figure 5 compares distributions of regional mean near-surface temperature trends consistent with the observed effects of anthropogenic and natural forcings (in red) with distributions of trends in the world that might have been if there had been no human influence on climate (in green). The likelihood of experiencing the observed trends (shown as the black lines in Figure 5) can then be compared in the two worlds (as represented by the red and green distributions). Human influence is estimated to have more than doubled the likelihood of positive warming trends in every region considered except central North America.

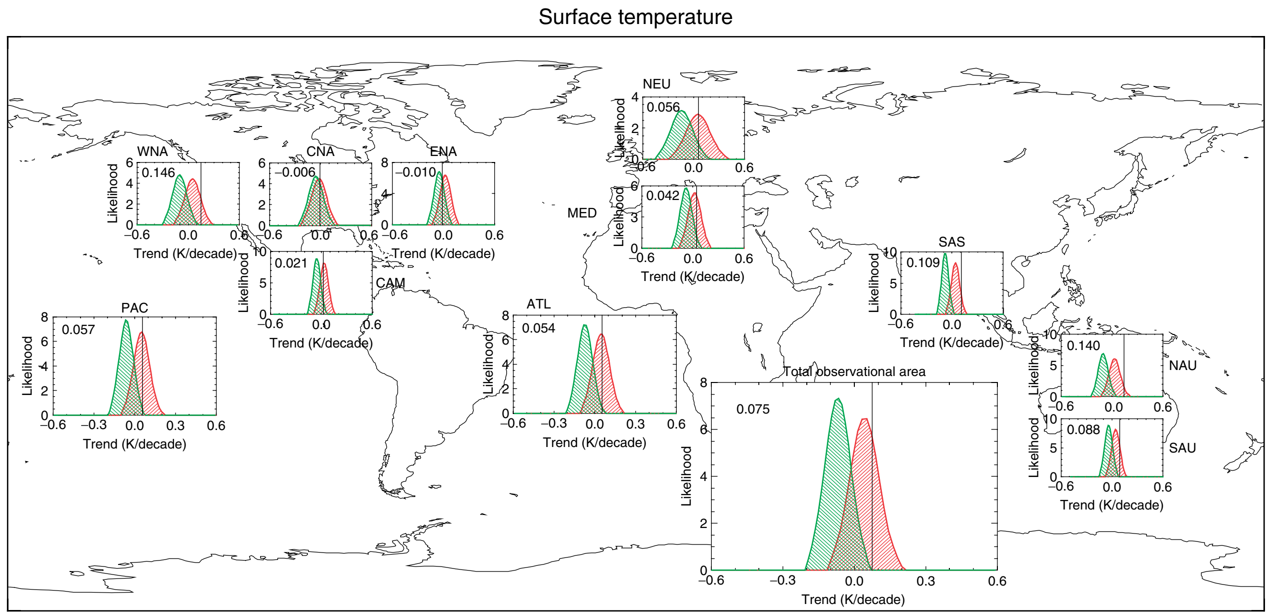

FIGURE 5 | Distributions of near-surface temperature trends during 1950–1997 in different regions constrained by the global analysis in a climate forced with both anthropogenic and natural forcings (red lines) and with natural forcings only (green lines). The y axis gives the normalized likelihood. The observed trend in each region is marked on each panel as a black line. The regions are South Australia (SAU), North Australia (NAU), Central America (CAM), western North America (WNA), central North America (CAN), eastern North America (ENA), Mediterranean Basin (MED), northern Europe (NEU), South Asia (SAS), Atlantic (ATL), and Pacific (PAC). Their geographical extents are defined in Christidis et al. (2009).

HYDROLOGICAL CYCLE

Theoretical Understanding of How the Hydrological Cycle Responds to Anthropogenic Warming

The water holding capacity of the lower troposphere increases in a warmer world, as does the amount of water vapor in the lower troposphere. According to the Clausius–Clapeyron (CC) relation, the saturation vapor pressure increases exponentially with temperature. As moisture condenses out of supersaturated air from time to time, it is physically plausible, and has been assumed in many studies, that the distribution of relative humidity would remain roughly constant under climate change. In this case, the CC-relation implies a roughly exponential increase with temperature in specific humidity at a rate of about 7%/K.[45] The direct consequences of such a water vapor increase would include a decrease in convective mass flux, an increase in horizontal moisture transport, associated enhancement of the pattern of evaporation minus precipitation and its temporal variance, and a decrease in horizontal sensible heat transport in the extratropics. An anticipated consequence of these flux and transport changes is that wet regions should become wetter and dry regions drier.[46] Many of these anticipated changes, reasoned from physical principles, have been observed and confirmed by climate model simulations.

Atmospheric Humidity

Lack of appropriate data has been a significant limiting factor in the analysis of humidity changes, although there has been some recent progress with the development of the HadCRUH Surface Humidity dataset.[47,48] HadCRUH (as shown in Figure 6) indicates significant increases between 1973 and 2003 in surface-specific humidity over the globe, the tropics, and the Northern Hemisphere, with consistently larger trends in the tropics and in the Northern Hemisphere during summer, and negative and nonsignificant trends in relative humidity. This is in accord with the CC-relation: warmer regions should exhibit larger increases in specific humidity for a given temperature change. Anthropogenic influence has been clearly detected in this surface humidity dataset.[47] The anthropogenic water vapor fingerprint simulated by an ensemble of 22 climate models has also been identified in lower tropospheric moisture content estimates derived from SSM/I data covering the period 1988–2006.[49]

Precipitation

The availability of energy is a stronger constraint than the availability of moisture on the increase of global precipitation.[45] Mitchell et al.[50] theorized that the latent heat of condensation in the troposphere

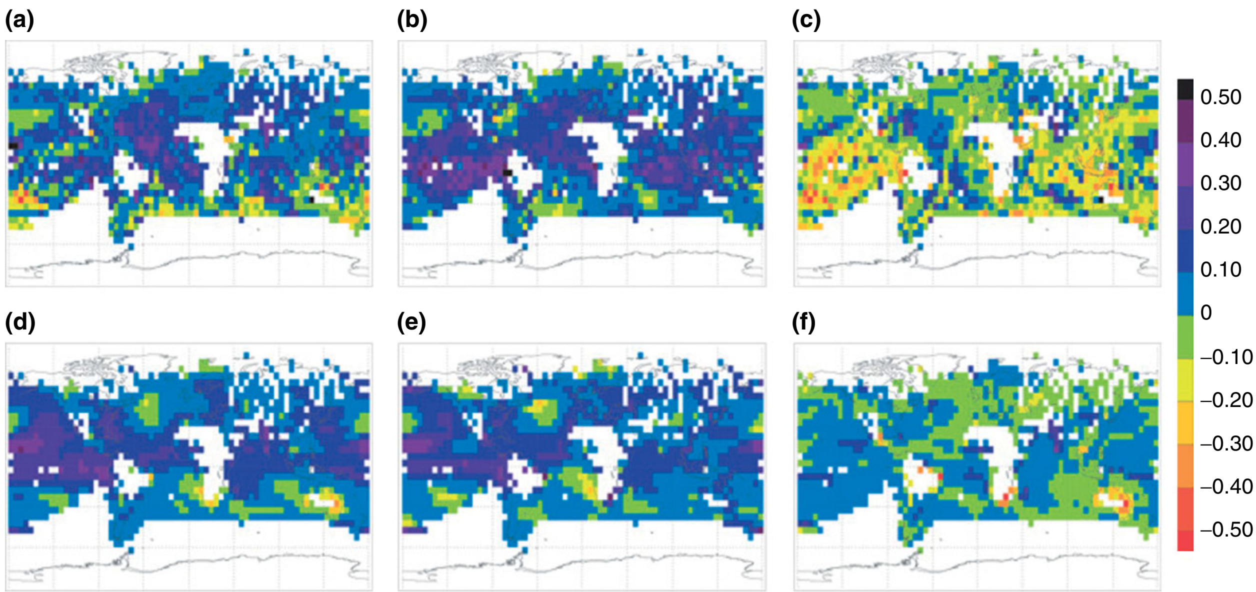

FIGURE 6 | Observed (top row) and simulated (bottom row) trends in specific humidity over the period 1973–1999 in grams per kilogram per decade. Observed specific humidity trends (a) and the sum of trends simulated in response to anthropogenic and natural forcings (d) are compared with trends calculated from observed (b) and simulated (e) temperature changes under the assumption of constant relative humidity; the residual actual trend minus temperature induced trend is shown in (c) and (f). Adapted from Willett et al.[47]

is balanced by radiative cooling. Warming the troposphere enhances the cooling rate, thereby increasing precipitation but this could be partly offset by a decrease in the efficiency of radiative cooling due to an increase in atmospheric greenhouse gases. As a result, global precipitation rates are expected to increase only at around 2%/K in General Circulation Model (GCM)s rather than following the 7%/K of the CC relationship. Wentz et al.,[51] using a relatively short 20-year SSM/I record, suggest that observed global precipitation has increased according to the much faster CC-relation, but Liepert and Previdi[52] show that 20 years may not be sufficient to determine whether models and observations agree on the rainfall response to global warming. This is because of various problems with observational data and because global precipitation change estimated over such a short time period may not be representative of changes that will occur on longer timescales. Observed changes in globally averaged land precipitation appear to be more consistent with the expected effects of both anthropogenic and natural forcings (including volcanic activity that affects short wave forcing) than with the effects of long wave forcing in isolation.[53,54]

Another expected aspect of simulated precipitation change is a latitudinal redistribution of precipitation including increasing precipitation at high latitudes and decreasing precipitation at subtropical latitudes, and potentially changes in the distribution of precipitation within the tropics by shifting the position of the Intertropical Convergence Zone. Comparisons between observed and modeled trends in land precipitation over two periods during the 20th century are shown in Figure 7. A comparison of observed trends averaged over latitudinal bands with those simulated by 14 climate models forced by the combined effects of anthropogenic and natural external forcing, and by 4 climate models forced by natural forcing alone, shows that anthropogenic forcing has had a detectable influence on observed changes in average precipitation.[55] While these changes cannot be explained by internal climate variability or natural forcing, the magnitude of change in the observations is greater than simulated.

The influence of anthropogenic greenhouse gases and sulfate aerosols on changes in precipitation over high-latitude land areas north of 55°N has also been detected.[56] Detection is possible here, despite limited data coverage, in part because the response to forcing is relatively strong in the region, and because internal variability is low, as is expected in dry regions. Consistent with this argument, there has been some consistency in northern Europe winter precipitation between that from observations and that from simulations conducted by four different regional climate models.[38] Generally, however, detection and attribution of regional precipitation changes remains difficult because of low signal-to-noise ratios and poor observational coverage. To date there have been no

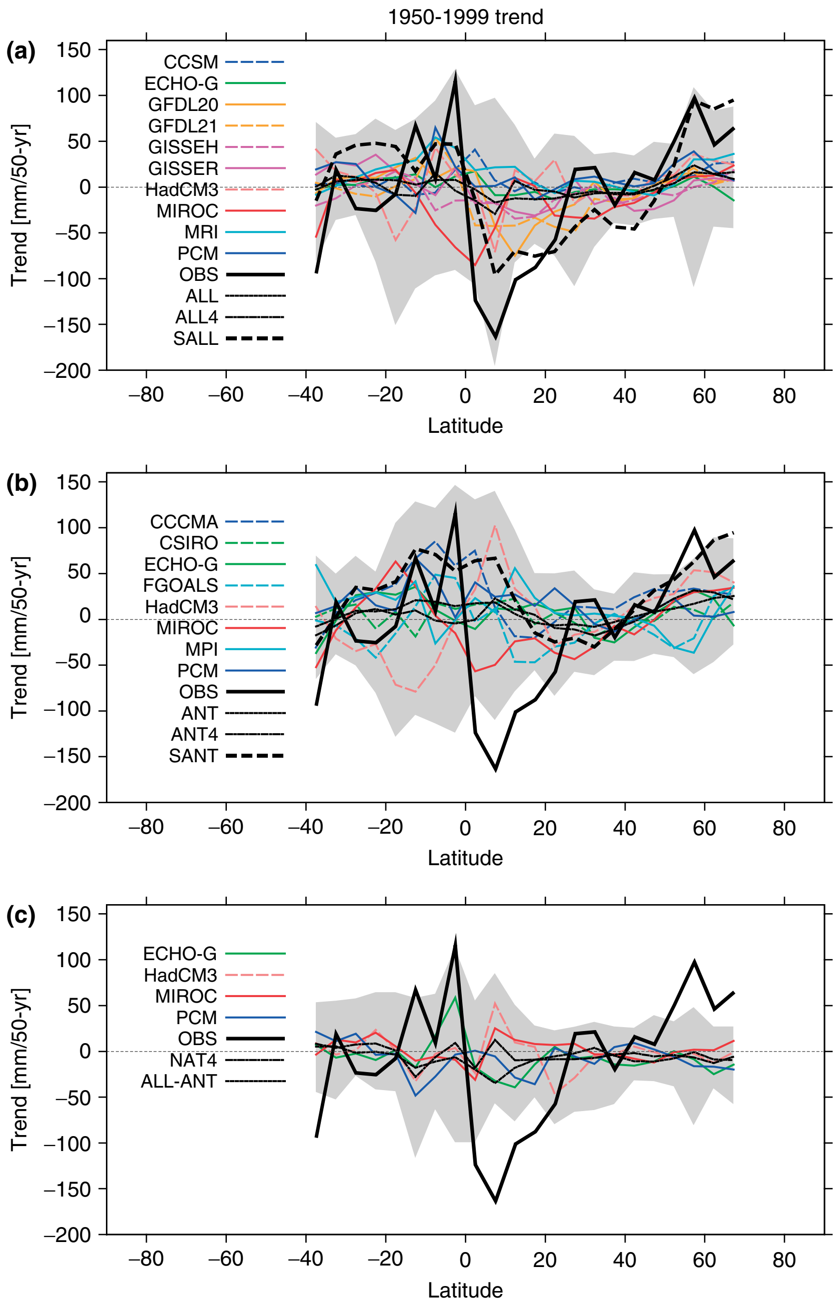

FIGURE 7 | Observed (solid black) and simulated zonal-mean land precipitation trends for 1950–1999. Black dotted lines indicate the multimodel mean from all available models (including both anthropogenic and natural forcings (denoted ALL) in (a), anthropogenic forcings only (ANT) in (b), and natural forcings only (NAT) as represented by ALL–ANT in (c), and black dashed-dotted lines from the subset of four models that simulated the response to each of the forcing scenarios (ALL4, ANT4, and NAT4). The model-simulated range of trends is shaded. Black dashed lines indicate ensemble means of ALL and ANT simulations that have been scaled (SALL and SANT) to best fit the observations based on a one-signal analysis. Colored lines indicate individual model mean trends.

detection and attribution studies of precipitation over oceans because the available satellite datasets (such as that from the SSM/I) are short and not considered to be sufficiently reliable for this purpose.

Runoff Change and Drought

Monitoring and understanding changes in runoff and drought is more difficult than for temperature and precipitation because soil moisture is poorly observed, and soil moisture and runoff changes are difficult to constrain from the residual difference between precipitation and evaporation, both of which are also relatively poorly observed. Many factors can cause soil moisture and runoff changes, including changes in climate, land use, stream management, water withdrawal, and water use efficiency by plants in high CO_2 environments ([57]). Nevertheless, there has been an overall global increase in dry areas, as represented by the Palmer Drought Severity Index (PDSI), a commonly used meteorological drought indicator, and this increase has been attributed to anthropogenic influence.[58] It should be noted that the calculation of PDSI involves changes in both surface temperature and precipitation but is dominated by changes in temperature, and therefore, detection in PDSI is largely associated with increased temperatures rather than changes in precipitation.

Despite more intensive human water consumption, continental runoff has increased through the 20th century. Gedney et al.,[57] using a surface exchange scheme driven by observations and climate model simulations, detect anthropogenic influence on global runoff. They attribute the observed increase in runoff to a suppression of plant transpiration resulting from CO_2-induced stomatal closure[57] although it has been argued that data limitations call the conclusions of this study into question.[57,59]

In climates where seasonal snow storage and melting plays a significant role in annual runoff, the hydrologic regime changes with temperature. In a warmer world, less winter precipitation falls as snow and the melting of winter snow occurs earlier in spring, resulting in a shift in peak river runoff to winter and early spring. This has been observed in the western US[60] and in Canada.[61] The observed trends toward earlier 'center' timing of snowmelt-driven streamflows in the western US since 1950 are detectably different from natural variability.[62] A recent detection study of change in the hydrological cycle of the western US attributes up to 60% of observed climate related trends in river flow, winter air temperature, and snow pack over the 1950–1999 period in the region to human influence.[63]

Cryosphere

Among the varios parameters characterizing changes in snow cover, snow cover duration has the strongest sensitivity to variations in climate.[64] Maritime climates with extensive winter snowfall (e.g., the coastal mountains of western North America) are most sensitive and continental interior climates with relatively cold, dry winters are least sensitive. The largest observed decreases in snow cover duration are concentrated where seasonal mean air temperatures are within 5°C of zero, a zone which extends around the midlatitudinal coastal margins of the continents. Climate model simulations of the 20th century show snow cover changes similar to those observed.[64] There has been a reduction in the ratio of precipitation falling as snow in the western US that cannot be explained by climate models including only the natural effects of solar and volcanic forcings and which has been attributed to anthropogenic forcings.[63,65]

Decreases in Arctic sea ice, shown in Figure 8, are seen in both observations and in climate model simulations including anthropogenic forcings,[66] although few model simulations show trends in sea ice extent of comparable magnitude to observations.[67] Human influence on Arctic sea ice decline is detectable in an optimal detection analysis[68] and could have been detected as early as 1992, well before the last recent dramatic sea ice retreat. In addition, the anthropogenic signal is also detectable for individual months from May to December, suggesting that human influence, strongest in late summer, now also extends into colder seasons.[68] In contrast, Antarctic sea ice has not significantly decreased.

CIRCULATION CHANGES

Two of the major global modes of variability are the NAM and SAM. Upward trends in these modes have been shown to be inconsistent with simulated internal variability (Hegerl et al.[2] and references cited therein).

While the NAM trend is larger than that simulated in many climate model simulations,[69] the trend in the SAM is consistent with simulated trends in simulations including greenhouse gas increases and stratospheric ozone depletion.[70] However, model simulations can show positive trends in the annular modes at the surface, but negative trends higher in the atmosphere, and it has been argued that anthropogenic circulation changes are poorly characterized by trends in the annular modes.[71]

Until recently, formal detection and attribution analyses of sea level pressure (SLP) have been restricted to individual seasons,[72–74] and while these studies all detected the influence of external forcing on SLP, none of them were able to separately detect the effects of anthropogenic and natural influences. Recently, Gillett and Stott[75] carried out a detection and attribution analysis using SLP from all four seasons over the 60-year period 1949–2009. Observed SLP, taken from HadSLP2,[76] was compared with output from two ensembles of simulations of HadGEM1.[77,78] The first included anthropogenic greenhouse gases, aerosols, and stratospheric ozone depletion (ANT), and the second ensemble also included volcanic aerosol and solar variability (ALL).

Figure 9 shows linear trends in zonal-mean SLP for each season over the period 1949–2009 in observations and the ALL ensemble. As expected, the largest trends are observed in DJF, with decreases in SLP over the Arctic and Antarctic. However, one aspect of the trend pattern which has not received much attention is the significant increase in SLP observed in all latitude bands between 32.5°N and 62.5°S.[75] An increase in SLP is also simulated in all these latitude bands. The signal-to-noise ratio of

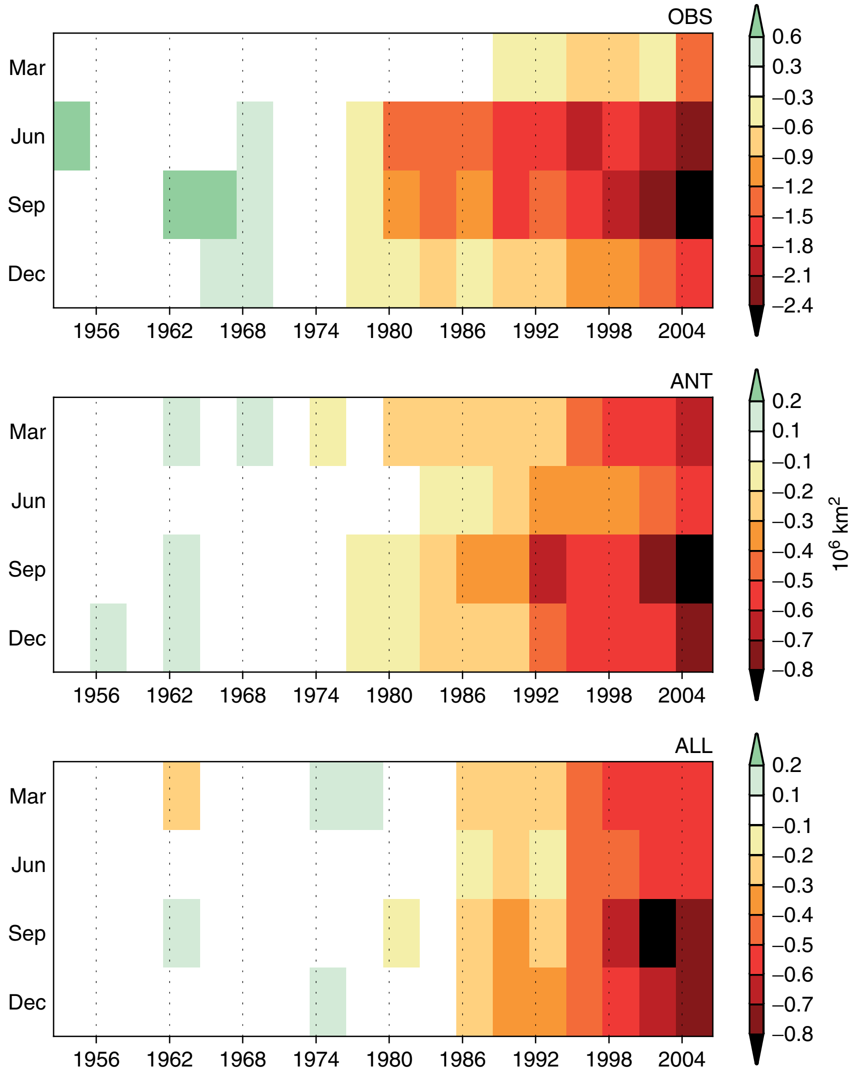

FIGURE 8 | Seasonal evolution of observed and simulated Arctic sea ice extent (ASIE) over 1953–2006. ASIE anomalies relative to the respective 1953–1982 means from observations (OBS) and 20C3M model simulations with anthropogenic only (ANT) and natural plus anthropogenic (ALL) forcings are plotted. Adapted from Min et al.[68]

these trends is generally higher than for the high-latitude trends, due to better sampling and lower internal variability. The other seasons generally show a similar pattern of trends to that seen in DJF, with decreases simulated and observed in the polar regions and increases at low latitudes, particularly, in the midlatitudes of the Southern Hemisphere.

Gillett and Stott[75] applied a detection and attribution analysis using 5-year mean SLP in the seven latitude bands shown and for each of the four seasons. They were able to detect an anthropogenic response independently of the natural response and with an amplitude consistent between model and observations. These results suggest that while models may fail to reproduce SLP trends in DJF over the high northern latitudes,[70,73] a more complete analysis considering all regions and seasons does not find a significant bias in the amplitude of the simulated SLP response to external forcing.

Some evidence has been found for changes in atmospheric storminess. The trend pattern in atmospheric storminess as inferred from geostrophic wind energy and ocean wave heights has been found to contain a detectable response to anthropogenic and natural forcings with the effect of external forcings being strongest in the winter hemisphere.[74]

OCEANIC CHANGES

It has been estimated that over 80% of the excess heat built up in the climate system by anthropogenic forcing has accumulated in the global oceans[79] and therefore it is important to understand oceanic variability and changes since uptake of heat by the ocean acts to mitigate transient surface temperature rise. The IPCC AR4 report concluded that the warming of the upper ocean during the latter half of the 20th century was likely due to anthropogenic forcing.

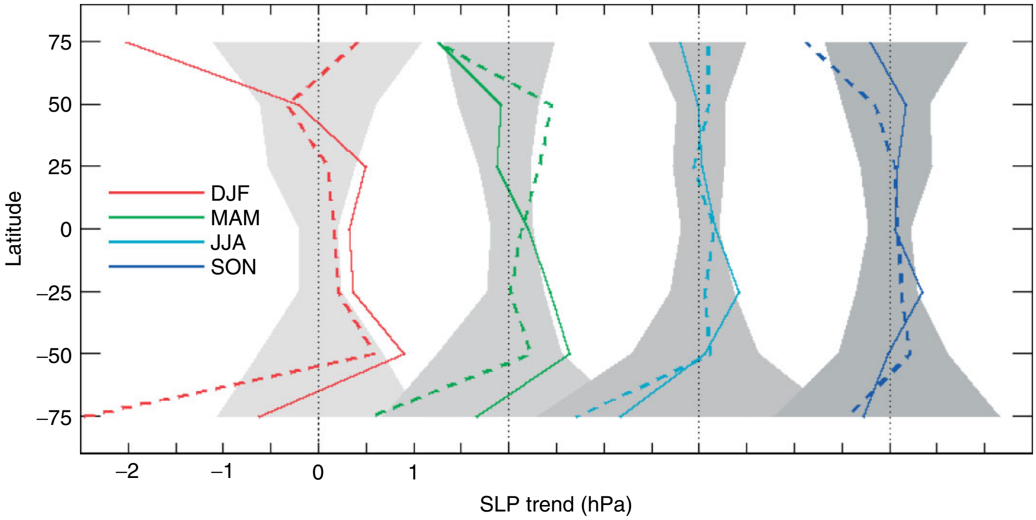

FIGURE 9 | Trends in seasonal mean sea level pressure in seven 25°-latitude bands between 87.5°S and 87.5°N calculated from 5-year means over the period December 1949–November 2009. Solid lines show observed trends from HadSLP2, and dashed lines show ensemble mean trends in the ALL simulations of HadGEM1. Gray bands represent the approximate 5–95% range of simulated SLP trends in a control simulation of HadGEM1. MAM, JJA and SON trends are offset from DJF trends by 2, 4 and 6 hPa, respectively. Vertical dotted lines indicate zero trend for each season. Adapted from Gillett and Stott.[75]

This conclusion was based largely on the studies of Barnett et al.[80] and Pierce et al.[81] who extended previous detection and attribution analyses of ocean heat content changes,[82,83] to a basin by basin analysis of the temporal evolution of temperature changes in the upper 700 m of the ocean and who detected a human-induced warming of the world's oceans with a complex vertical and geographical structure. However, while there was very strong statistical evidence that the warming could not be explained by internal variability as estimated by two different climate models, there were discrepancies between observed and modeled estimates of global ocean heat content variability. A large part of this discrepancy has now been seen to be associated with instrumental errors,[84] and there is much improved agreement when these bias corrections are included in observational datasets.[85]

However, the subsurface ocean has been sparsely observed in many regions, and sampling errors remain an issue when comparing observed and modeled timeseries of ocean properties, with the choice of infilling method being potentially important in poorly sampled regions.[86,87] A novel process-based technique for comparing models and observations has been proposed,[88,89] which separates ocean warming into a component largely associated with changes in air–sea heat flux (the temperature above the 14C isotherm) and a component largely associated with advective redistribution of heat (the depth of the 14C isotherm). This provides a clearer picture of the drivers of oceanic temperature changes. Figure 10, from Palmer et al.,[90] shows that the HadCM3 climate model captures in remarkable detail the temporal evolution of ocean temperatures in the World's ocean basins over the last five decades. By comparing space time patterns averaged over nonoverlapping 2-year periods for five different ocean basins, Palmer et al.[90] detected the effects of both anthropogenic and volcanic influences simultaneously in the observed record. This provided an advance on previous studies by attributing the short-term cooling episodes to volcanic eruptions and the multidecadal warming to anthropogenic forcing.

The other major property of ocean water masses is their salinity. Changes in salinity are of interest because they integrate changes in precipitation and evaporation at the surface and could therefore help better understand changes in the hydrological cycle over the sparsely observed ocean. It has been suggested that freshening at high latitudes is consistent with observed increases in precipitation at high latitudes[91] although climate model studies suggest that Atlantic freshening could be associated with changes in northward advection associated with variability of the meridional overturning circulation.[92] An optimal detection analysis of Atlantic salinity changes by Stott et al.[93] detected a human influence on the observed increases in salinity at low latitudes but found that high-latitude changes, including a recent reversal of the freshening observed previously, are consistent with internal variability.

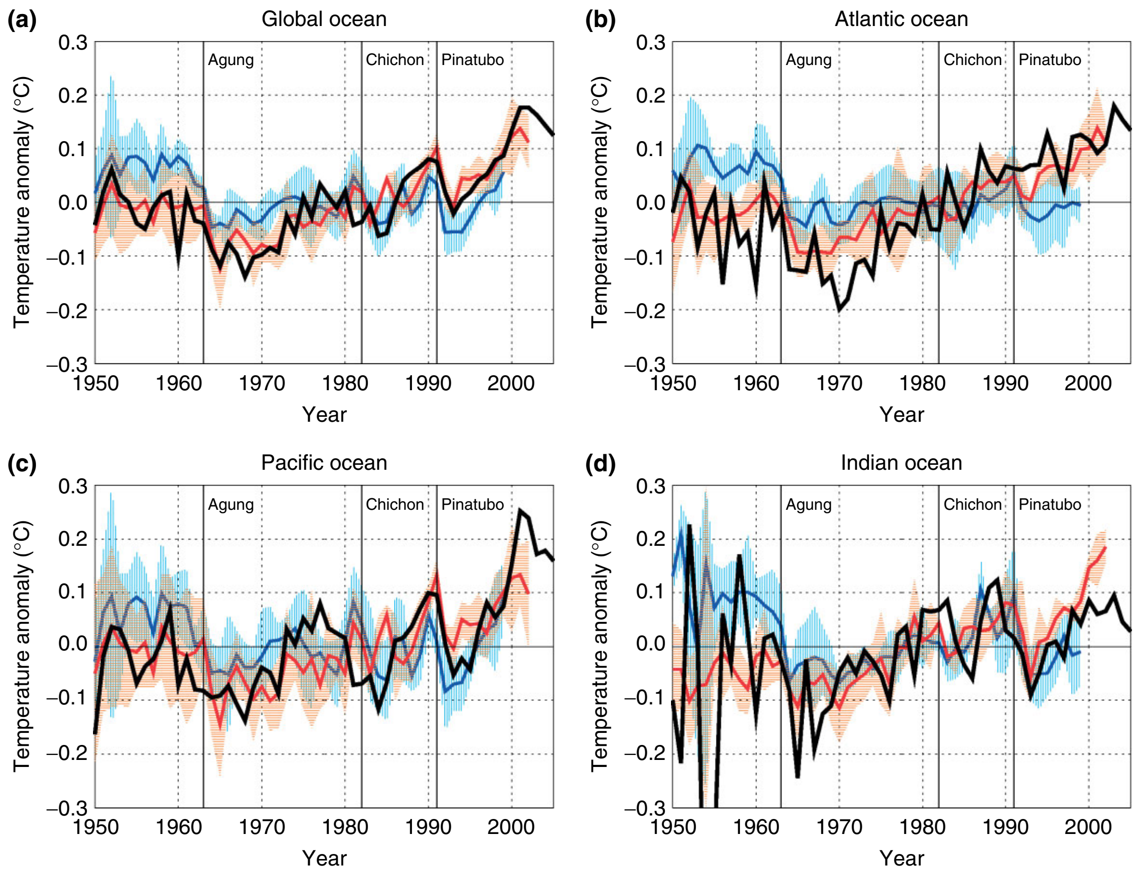

FIGURE 10 | Time series of global ocean temperature above the 14°C isotherm relative to 1950–1999 average for (a) global ocean, (b) Atlantic Ocean, (c) Pacific Ocean, and (d) Indian Ocean. Shown are the observations (black); the ensemble average of four HadCM3 simulations including both anthropogenic and natural forcings (red) and ensemble standard deviation (orange shading); and the ensemble average of four HadCM3 simulations including only natural forcings (blue) and ensemble standard deviation (light blue shading). The model data have been regridded and subsampled to match the observational coverage. The vertical lines show the approximate timing of the major volcanic eruptions. Adapted from Palmer et al.[90]

A major research topic remains an improved understanding of the rate of global sea level rise and its contributions from thermal expansion and melting of land ice, and a reduction in uncertainty in predictions of the geographical patterns of sea level rise. Future progress in attributing ocean changes could be made by considering water masses properties.[94,95] By considering temperature and salinity changes on density surfaces, it could be possible to better quantify the effects of anthropogenic and natural forcings on ocean heat content and better quantify the extent to which external forcings have altered the hydrological cycle over the oceans.[96,97]

EXTREMES

Many analyses of changes in extremes have focused on globally collected indices of climate extremes which summarize overall characteristics of extremes and are derived from high resolution data (see, e.g., Alexander et al.[98]). Observed changes in such indices are broadly consistent with changes expected with global warming; only with the inclusion of anthropogenic forcing can models reproduce the observed changes in frost days, growing season length, the number of warm nights in a year, and a heat wave intensity index.[99] An observed precipitation intensity index also appears to track simulated changes.[100]

Rather than analyze indices, Christidis et al.[101] analyzed the daily temperature dataset of Caesar et al.[102] and found a significant human influence on the observed warming of the warmest night of the year as well as on warming of the coldest days and nights of each year. However, they did not detect a significant change in the temperature of the hottest day of the year. Extremes of daily maximum temperatures show distinct regional patterns. Recent research suggests that some of these regional trends could be related to regional processes and forcings.

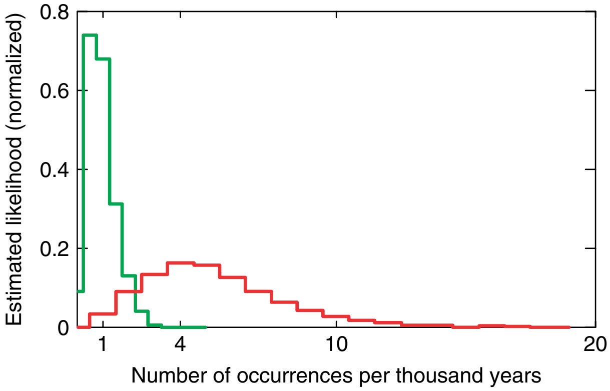

FIGURE 11 | Change in probability of mean European summer temperatures exceeding the 1.6 K threshold showing histograms of frequency of such events under late 20th century conditions in the absence of anthropogenic climate change (green line) and with anthropogenic climate change (red line). From Stott et al.[105] The distributions represent the uncertainty in this calculation's estimate of the frequencies of such events in the two cases.

For example, Portmann et al.[103] demonstrated that the rate of increase in the number of hot days per year in late spring in the Southeastern US over recent decades is significantly inversely proportional to climatological precipitation. They speculate that changes in biogenic aerosols resulting from land use changes could be responsible.

In addition to analyzing trends in extremes, a new framework has been developed for attributing individual extreme events. In such a framework, as elucidated by Allen,[104] the change in the probability of an extreme event under current conditions is calculated and compared with the probability of the event if the effects of particular external forcings, such as due to human influence, had been absent. In such a way Stott et al.[105] showed that the probability of seasonal mean temperatures as warm as those observed in Europe in 2003 had very likely at least doubled as a result of human influence (see Figure 11). The same general approach could, in theory, be applied to other extreme weather events such as floods or droughts, in order to determine whether the probability of a particular event has changed as a result of a chosen set of climate forcing factors, although in practice this will require models capable of capturing the relevant processes.

Attributing causes to changes in the frequency and intensity of hurricanes has remained very controversial. Two studies,[106,107] have shown that human-caused changes in greenhouse gases are the main driver of the observed 20th-century increases in sea surface temperatures in the main hurricane formation regions of the Atlantic and the Pacific. However, the importance of the anthropogenic increase in sea surface temperature in the cyclogensis region for past and future changes in hurricane activity is still poorly understood.[108] The limitations of the observed database and of current climate models in resolving processes relevant for hurricanes make progress in this field difficult at present.

In conclusion, while there has been progress since AR4, there are still many gaps in our understanding of changes in extremes and in our ability to attribute observed changes to particular causes. Changes in temperature extremes have proven to be more interesting and difficult than an assumption of a shift of the distribution would lead to expect, particularly so for daily maxima.[103] While attribution of change in precipitation extremes is made difficult by the lack of tools for reliable comparison of models with observations, perfect model studies indicate that changes in precipitation extremes should be detectable at least on large scales.[109]

CONCLUSION

The wealth of attribution studies reviewed in this article shows that there is an increasingly remote possibility that climate change is dominated by natural rather than anthropogenic factors. Progress since the AR4 has shown that discernible human influence extends to reductions in Arctic sea ice and changes in the hydrological cycle associated with increasing atmospheric moisture content, global and regional patterns of precipitation changes, and increases in ocean salinity in Atlantic low latitudes. In addition, changes in Antarctic temperatures (the one continent on which an attribution study was not available at the time of AR4) have been attributed to human influence and there is increasing evidence that human influence on temperature is becoming significant below continental scales, as would be expected from the large-scale coherence of surface temperature. We have discussed in this review how attributed changes in atmospheric moisture content[49] and precipitation patterns[55] are consistent with theoretical expectations.[45,46]

At times, attribution studies can highlight differences between models and observations that challenge our understanding and require further investigation. Major challenges still remain in obtaining robust attribution results at the regional scales needed for evaluation of impacts. Climate models often lack the processes needed to realistically simulate regional details. In addition, observed changes in non-climate quantities could be the result of additional influences besides climate, thus complicating attribution studies. Extremes pose a particular challenge, since rare events are, by definition, poorly sampled in the historical record, and many challenges remain for robustly attributing regional changes in extreme events such as droughts, floods, and hurricanes.

Nevertheless, successful adaptation would benefit from improved information about societal vulnerability in a changing climate.[110] We have discussed here how the changed likelihood of a particular weather event can be attributed to human influence, and in principle, such a concept could be applied to any extreme weather event and its associated impacts. Models of higher resolution will likely be required to resolve processes responsible for events such as floods. Atmosphere only models, constrained by prescribed sea surface temperatures, can be used to address the causes of specific events, although atmosphere–ocean coupling and the causes of the sea surface conditions also need to be considered.

Above all, understanding observed changes is an essential prerequisite for successful forecasting of future changes. Further research on the use of observational constraints has the potential to reduce the large spread from modeling uncertainty, some of which could be slow to reduce purely based on the improvement of model formulation. Thus this suggests two key benefits from attribution studies for improving climate model predictions. First, by finding robust relationships between observed quantities and predictor variables, attribution studies can be used to obtain observationally constrained estimates of uncertainties in future changes. This approach has been applied to global mean surface temperature but further research is needed to extend this approach to regional scale temperatures and other variables. Second, attribution studies, by identifying model data differences that are outside the range expected from natural internal variability, have the potential to highlight inadequacies in model forcing or formulation or problems with observational datasets. In some instances, better representation of regional changes in models might require inclusion of hitherto neglected forcings or better representation of crucial processes. In others, efforts may be needed to better account for errors and systematic biases in observational data.

ACKNOWLEDGEMENTS

P.A.S. was supported by the Joint DECC and Defra Integrated Climate Programme—DECC/Defra (GA01101). The authors acknowledge the support of the International Detection and Attribution group by the US department of Energy's Office of Science, Office of Biological and Environmental Research and the US National Oceanic and Atmospheric Administration's Climate Program Office.DAS was funded by Microsoft Research.

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