A Review of Climate Change Attribution Studies

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ABSTRACT

This paper reviews recent progress in climate change attribution studies. The focus is on the attribution of observed long-term changes in surface temperature, precipitation, circulation, and extremes, as well as that of specific extreme weather and climate events. Based on new methods and better models and observations, the latest studies further verify the conclusions on climate change attribution in the IPCC AR5, and enrich the evidence for anthropogenic influences on weather and climate variables and extremes. The uncertainty of global temperature change attributable to anthropogenic forcings lies in the considerable uncertainty of estimated total radiative forcing due to aerosols, while the uncertainty of precipitation change attribution arises from the limitations of observation and model simulations along with influences from large internal variability. In terms of extreme weather and climate events, it is clear that attribution studies have provided important new insights into the changes in the intensity or frequency of some of these events caused by anthropogenic climate change. The framing of the research question, the methods selected, and the model and statistical methods used all have influences on the results and conclusions drawn in an event attribution study. Overall, attribution studies in China remain inadequate because of limited research focus and the complexity of the monsoon climate in East Asia. Attribution research in China has focused mainly on changes or events related to temperature, such as the attribution of changes in mean and extreme temperature and individual heat wave events. Some progress has also been made regarding the pattern of changes in precipitation and individual extreme rainfall events in China. Nonetheless, gaps remain with respect to the attribution of changes in extreme precipitation, circulation, and drought, as well as to the event attribution such as those related to drought and tropical cyclones. It can be expected that, with the continual development of climate models, ongoing improvements to data, and the introduction of new methods in the future, climate change attribution research will develop accordingly. Additionally, further improvement in climate change attribution will facilitate the development of operational attribution systems for extreme events, as well as attribution studies of climate change impacts.

Key words: climate change, detection and attribution, climate extremes, event attribution, optimal fingerprinting

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1. Introduction

The Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) stated that warming of the climate system is unequivocal, and it is extremely likely that human influence has been the dominant cause of the observed warming since the mid-20th century (IPCC, 2013). Warming has already caused noticeable consequences, such as the rapidly rising global mean surface temperature and consequent record-breaking high temperatures, changing precipitation patterns, melting ice sheets, and rising sea levels [National Academies of Sciences, Engineering, and Medicine (NAS), 2016]. These changes are bringing ever-growing influences to human society from different aspects. Among them, the impact that is most easily perceived by human society is that some types of extreme events are occurring more and more frequently and with increasing intensity (Seneviratne et al., 2012). In addition to considering changes in climate variables, the vulnerabilities of different regions and exposure to climate-related hazards need to be comprehensively considered to cope with the

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increasing climate change risks. Moreover, through a combination of adaptation strategies and climate change mitigation by reductions in greenhouse gas emissions, reducing such risks can be achieved (Stott et al., 2016). Detection and attribution are important means of assessing climate change and the risks it poses, as well as deepening our understanding of the impact of human activities on climate change. They are the science behind answering the question as to whether a change has occurred or whether the frequency and intensity of high-impact events have changed, as well as revealing the extent to which the detected change has been affected by different factors. Results from detection and attribution, especially for event attribution, can provide an important scientific basis for policymakers to formulate climate policies and adaptation strategies (Knutson et al., 2017).

"Detection" and "attribution" are two interconnected concepts in climate change, but there also exists a difference between them. Detection is defined as the process of demonstrating that climate has changed in some defined statistical sense, without providing a reason for that change. With regard to a detected change, the attribution of climate change is the process of evaluating the relative contributions of multiple causal factors to a change or event with an assignment of statistical confidence (IPCC, 2007; Hegerl et al., 2010; Stott et al., 2016). It can be seen from the definition that the attribution of climate change needs to combine statistical analysis with physical understandings, and is thus more complicated than detection (Allen et al., 2006; Hegerl et al., 2011). Attribution requires demonstrating that a detected change is "consistent with the estimated responses to the given combination of anthropogenic and natural forcing" and "not consistent with alternative, physically plausible explanations of recent climate change that exclude important elements of the given combination of forcings" (IPCC, 2001). Current attribution studies can be grouped into three general types: the attribution of long-term changes or trends of climate variables or extremes; the attribution of extreme weather or climate events; and the attribution of climate-related impacts (Knutson et al., 2017). The different subjects included in these three main types of attribution studies and their emergence times are shown in Fig. 1.

Since the 1990s, with the improvement of observational data (e.g., increased spatial and temporal coverage), the advancement of attribution methods, and the development of climate models and computing capabilities, attribution studies of climate change have made remarkable progress (Mitchell et al., 2001; Zhou et al., 2008; Wang et al., 2012; Bindoff et al., 2013; Sun et al., 2013). The Third Assessment Report of the IPCC clearly defines the two concepts of "detection" and "attribution" in climate change (IPCC, 2001). The IPCC's Fourth Assessment Report (AR4) reports that many observed changes in the climate system are attributable, and there is accumulating evidence that human influence is an important factor for global warming since the 1950s (IPCC, 2007). However, the attribution of climate change at regional scales and shorter time periods (less than 50 yr) remains a challenge (Hegerl et al., 2007). Compared to AR4, benefiting from more detailed observations and better climate models, AR5 states that attribution research can now quantify the contribution of human influence on detected changes in more climate system components. AR5 concludes that human influence has been detected in warming of the atmosphere and the ocean, in changes in the global water cycle, in reductions in snow and ice, in

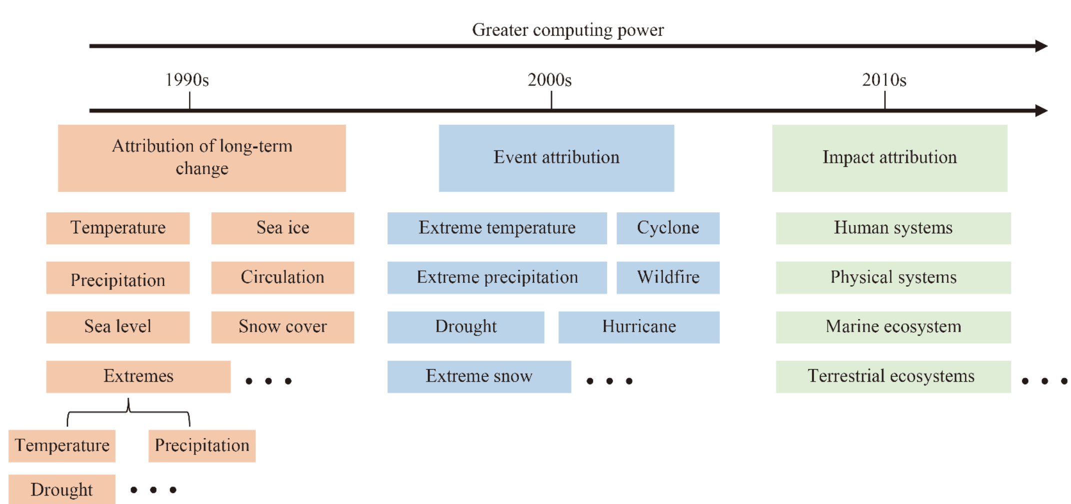

Fig. 1. The three main types of climate attribution studies along with their respective subjects and emergence times.

global mean sea level rise, and in changes in some climate extremes (IPCC, 2013). The climate variables involved in climate attribution research have been expanding, extending from temperature to precipitation and extremes, and even some variables related to typhoons (Bindoff et al., 2013; Sun et al., 2013). Moreover, in addition to global-scale studies, more and more attribution research has switched focus to regional scales (Barnett et al., 2005; Sun et al., 2013).

Before the 21st century, most attribution studies concentrated on analysis of the relationship between long-term changes in a climate variable or component and human influences. After Stott et al. (2004) published their attribution analysis of the heat wave event that occurred in Europe in 2003, the attribution of extreme weather events has progressed significantly. Since 2012, the *Bulletin of the American Meteorological Society* (BAMS) has published annually a supplementary special issue on the attribution of extreme events that occurred around the world in the previous year (Peterson et al., 2012, 2013; Herring et al., 2014, 2015, 2016, 2018). Some operational attribution systems are undergoing development in order to provide more timely attribution assessment of extreme events (NAS, 2016; Stott et al., 2016). In addition, the attribution of climate change impacts on humans and natural systems is also emerging (Smith et al., 2001; Rosenzweig et al., 2007). Whilst the field of impact attribution shares important features with the attribution of observed changes in the climate system, it is an area of far greater complexity. Detection and attribution of the impacts caused by climate change is a fundamentally cross-disciplinary issue, involving concepts, terms, and standards spanning the varied requirements of various disciplines (Stone et al., 2013). A detailed review of the attribution of the impact of climate change can be found in Stone et al. (2013).

The current paper reviews recent major advances and key findings from the attribution of long-term changes in climate conditions and event attribution studies, focusing on temperature, precipitation, circulation, and related extremes. Before reviewing the latest progress in attribution studies, the main methods of attribution will be first introduced. Moreover, the gaps in, and prospects for, the attribution of climate change will also be discussed, including a concise discussion on the current status and development of regional attribution research in China.

2. Methods employed in attribution studies

In recent years, to meet the requirements of attribution science, the methods used for detection and attribution have improved and developed considerably (Hegerl et al., 2010; Bindoff et al., 2013; Sun et al., 2013). Many attribution studies rely on simulations of climate models to determine the "fingerprint" of climate change and to address its uncertainty. Other studies use only observational data to distinguish between changes caused by radiative forcing and internal variability, and can obtain consistent conclusions compared with modeling approaches (Hegerl and Zwiers, 2011). Statistical techniques for the attribution of long-term changes in climate variables or extreme events based on models and observations can be broadly classified into two categories: multivariate analysis and Bayesian inference. The widely used optimal fingerprinting method belongs to the former, while the advantage of the latter lies in the capability to integrate multiple sources of data for attribution. When it is difficult to perform single-step attribution for a climate variable or phenomenon directly, some studies have instead carried out the attribution using multi-step methods based on the attribution of the change in climate conditions closely associated with that variable or phenomenon. The multi-step attribution method first attributes an observed change to changes in climate or other environmental conditions, and then separately attributes the changing climate or other environmental conditions to an external forcing, such as the anthropogenic emissions of greenhouse gases (Knutson et al., 2017). In addition, approaches for extreme event attribution are similarly manifold. However, each method has its own advantages and disadvantages compared to one another, and thus only several frequently used event attribution methods are introduced.

2.1 *Methods minimizing the use of climate models*

Some studies have attempted to avoid using models in the separation of externally forced change and variability. For example, the time series method separates the internal variability and external forcing by decomposing the timescale of signal and noise. Schneider and Held (2001) used the time series method to isolate low-frequency climate signals and variability on short timescales to identify long-term signals in observed surface air temperature changes. They found that large-scale warming can be clearly separated from changes in surface air temperature during the 20th century, especially in summer of the Northern Hemisphere; large-scale warming is consistent with the expected increase in greenhouse gas concentrations; and localized cooling is also found, indicative of the radiative effect of the sulfate aerosol emitted by human activities. With an adaptive signal processing technique, Qian (2016a) isolated multidecadal variability from the time series of temperature in eastern China for the past 100 years, and found that multi-decadal variability facilitates the warming in the early 20th century and contributes to about 1/3 of the warming in the past 30 years. Time series-based methods assume statistically significant differences between the changing modes resulting from external forcings and from the internal variability of the climate system. However, the internal variability of the climate system exists at any timescale (Hasselmann, 1976), and thus separation of time series based on timescales is incomplete.

Another example is Granger causality analysis. This method mainly infers causality between two variables by examining the lead–lag correlation between them, and attempts to control the influence of third-party variables that are related to these two variables (Granger, 1980). Let two time series be X and Y. Granger causality analysis determines whether X can predict Y through statistical tests. If it can, X is considered as the cause of Y, and vice versa. The test method is to judge whether the critical value of the F-statistic is greater than the standard value of the F distribution. If the probability of the critical value p is less than α, the null hypothesis that X is not the cause of Y can be rejected, i.e., X can lead to Y. Smirnov and Mokhov (2009) comprehensively used and compared traditional Granger causality analysis and long-term causality analysis methods for low-frequency changes and found that the increase in the CO_2 concentration was the dominant factor for the global average temperature rise in recent decades. Using Granger causality analysis, Stern and Kaufmann (2014) confirmed that human influence is partially responsible for observed global warming, and consequently global warming has a certain impact on the global carbon cycle.

2.2 *Optimal fingerprinting method*

The most widely used statistical attribution method that combines model simulations with observational data is the optimal fingerprinting method. The climate system generates unique responses to various external forcings, just as everyone has a unique fingerprint. The optimal fingerprinting method utilizes the apparent characteristics of the "fingerprint" for analysis and makes comprehensive comparisons between the simulated and observed climate changes. The optimal fingerprinting method uses the simulated responses of the climate system in spatial, temporal, and spatiotemporal modes to determine whether these responses are consistent with observations and if they are significantly larger than the internal variability of the climate system. The optimal fingerprinting method maximizes the signal-to-noise ratio by rotating the spatial field of the signal and noise. It can be used not only for detecting the signals of external forcings, but also for distinguishing mechanisms of different forcings (Hasselmann, 1997; Allen and Tett, 1999). The earliest statistical method used to obtain the fingerprint in the observed change is the pattern correlation method. This method mainly calculates the correlation coefficient between the expected and observed climate changes over multiple consecutive time periods. For example, through this method, Santer et al. (1996) concluded that the pattern similarity between the expected fingerprint in climate models and the observed temperature changes showed an increase during 1963–87, and they believed that it was likely that this trend was partly caused by human activities. Afterwards, the optimal fingerprinting method is usually implemented by generalized linear regression. The observed climate change ($\boldsymbol{Y}$) is considered as a linear combination of the response to external forcing ($\boldsymbol{X}$) and residual climate internal variability ($\boldsymbol{u}$):

$$\boldsymbol{Y} = \sum_{i=1}^{n} \boldsymbol{a}_i \boldsymbol{X}_i + \boldsymbol{u}, \tag{1}$$

where $\boldsymbol{Y}$ is the filtered observation record; the column vector of the $\boldsymbol{X}$ matrix contains the estimated response patterns to external forcing to be studied; and $\boldsymbol{a} = [a_1, a_2, a_3, \ldots, a_n]$ is the vector of the scaling factor, which is used to adjust the amplitudes of those patterns. Vector $\boldsymbol{u}$ can usually be assumed to be a Gaussian random vector of covariance matrix $\boldsymbol{C}$, i.e., $\boldsymbol{C} = \mathrm{Cov}(\boldsymbol{u})$, and then the best linear unbiased estimate (based on the least-squares method) of the scaling factor $\boldsymbol{a}$ is:

$$\boldsymbol{a} = \left(\boldsymbol{X}^{\mathrm{T}}\boldsymbol{C}^{-1}\boldsymbol{X}\right)^{-1}\boldsymbol{X}^{\mathrm{T}}\boldsymbol{C}^{-1}\boldsymbol{Y} = \left(\tilde{\boldsymbol{X}}^{\mathrm{T}}\tilde{\boldsymbol{X}}\right)^{-1}\tilde{\boldsymbol{X}}^{\mathrm{T}}\tilde{\boldsymbol{Y}}. \tag{2}$$

Matrices $\tilde{\boldsymbol{X}}$ and $\tilde{\boldsymbol{Y}}$ represent the signal patterns and observations, which are normalized by the internal variability of the climate to maximize the signal-to-noise ratio. The signal of the response to external forcing, the matrix $\boldsymbol{X}$, is usually obtained from the coupled model, the atmospheric model, or the simplified climate model such as the energy balance model. The internal variability $\boldsymbol{u}$ is usually calculated from the control experiment of the coupled model. A new statistical approach for attribution uses a method of hypothesis testing and additive decomposition rather than traditional linear regression (Ribes et al., 2017). This new method exploits the magnitudes of the response from model simulations, rather than using the simulated patterns from the model and using the regression method to obtain the scaling factor (magnitudes of responses).

2.3 *Methods for event attribution*

NAS (2016) summarizes the two main methods used for the attribution of extreme weather and climate events: (1) using observational data to estimate changes in the probability and intensity of extreme weather and climate events with a certain intensity; and (2) using simulations of a climate model to compare the differences in extreme weather and climate events under climate conditions that are affected and not affected by human activities. The current paper mainly introduces the methods that make use of climate models for event attribution, which often relies on coupled climate models or atmospheric models. Coupled general circulation models (GCMs) provide the most comprehensive simulations of the climate system, including not only the atmosphere, ocean, sea ice, and land surface, but also biological and chemical processes such as the carbon cycle (Stott et al., 2016). The most commonly used coupled model data are the various simulations provided by phase 5 of the Coupled Model Intercomparison Project (CMIP5) (Taylor et al., 2012). Based on simulations from GCMs, the simplest way to implement attribution is to compare the model's simulations driven by different forcings with observations for a class of extreme weather events. This direct comparison requires two sets of model experiments: simulations including both anthropogenic and natural forcings ("actual world") and simulations without human influence ("counterfactual world"). For a certain type of extreme events, the contribution of human influence to the risk of change in such extreme events can be calculated based on the distribution of the climate variables related to the extreme events or an index that characterizes the extreme events in the two sets of simulations. The probability of a certain type of extreme events simulated under both anthropogenic and natural forcings is denoted as P_1, and the probability of such extreme events with only natural forcing is denoted as P_0. Then, the ratio P_1/P_0 is the risk ratio and $(1 - P_1/P_0)$ is the fraction attributable risk, which are used to measure the extent of human influence on the changes in probability or intensity of such extreme events (Allen, 2003; Stott et al., 2004; Fischer and Knutti, 2015). This method has been extensively used for attribution studies of temperature and precipitation extremes (Stott et al., 2016; Herring et al., 2018).

Compared to coupled models, atmosphere-only GCMs (AGCMs) are based on prescribed sea surface temperature (SST) and sea ice, and mainly simulate the forced changes in atmospheric composition. In an AGCM, the observed SST and sea ice, or simulated ones forced by both anthropogenic and natural forcings, are used to drive simulations representing the "actual" world, while the "counterfactual" world is simulated by using constant SSTs or SSTs without human influence. AGCMs are cheap to run, and thus can output simulations of more ensemble members, which are often used in event attribution studies. The newly updated Met Office Hadley Centre system (HadGEM3-A-N216; Walters et al., 2017) for the attribution of extreme weather and climate events is an AGCM. The HadGEM3-A-N216 uses observed SSTs and sea-ice data (HadISST, Rayner et al., 2003) as boundary conditions to simulate the "actual" world, while HadISST observational data minus an estimate of the anthropogenic contribution derived from CMIP5 model simulations is used to drive "natural" simulations. This attribution system has been widely used in event attribution (Burke and Stott, 2017; Li C. X. et al., 2017; Qian et al., 2018). Figure 2 shows an example of event attribution making use of a climate model. Based on the differences in the risk of extreme precipitation at a certain threshold between the two sets of simulations with and without human influence, the role of human activities on the extreme precipitation event can be discerned.

3. Attribution of long-term changes in the climate variables

3.1 *Mean surface temperature*

The climate change signals caused by external forcing at the global scale are easiest to obtain from instrumental surface air temperature and SST records (Jones and Moberg, 2003). Such data are characterized by high quality and broad temporal and spatial coverage, and have been extensively verified and evaluated, making them particularly suitable for climate change research (IPCC, 2001; Barnett et al., 2005). Therefore, detection studies were initially concentrated on changes in global surface temperature. In the development of previous IPCC assessment reports, due to the continuous improvement of observational data, models, attribution methods, and climate forcing simulations, the reliability of relevant conclusions on the detection and attribution of global temperature changes is increasing. Based on Had-CRUT4 and multi-model means, multiple regression analyses indicate that the observed global temperature changes show robustly detected responses to greenhouse gases for both periods of 1861–2010 and 1951–2010 (Gillett et al., 2013; Jones et al., 2013; Ribes and Terray, 2013). Attribution studies using other methods, such as simple statistical models and Granger causality methods, further confirm the obtained attribution conclusions of global

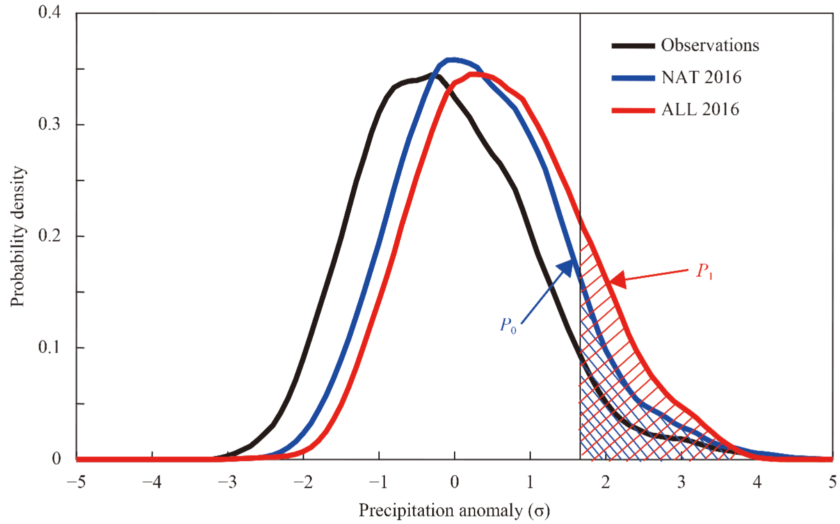

Fig. 2. Probability density functions of the May monthly precipitation anomaly for the northern part of the lower reaches of the Yangtze River. The red line corresponds to the HadGEM3-A-N216 all-forcings run (ALL) for 2016, while the blue line corresponds to natural forcings (NAT) for 2016, and the black line to observations over 1961–2013. The vertical line is the standardized observed precipitation anomaly of May 2016, which is chosen as the threshold. The blue and red hatchings show the probabilities of exceeding the threshold for precipitation as intense as in May 2016 under natural (P_0) and all forcings (P_1) respectively (adapted from Li C. X. et al., 2017).

mean temperature (Smirnov and Mokhov, 2009; Drost and Karoly, 2012). Based on AR4 and the results of these attribution studies, AR5 further enhances the attribution conclusions in AR4 on global average temperature, reporting that "it is extremely likely that more than half of the observed increase in global average surface temperature from 1951 to 2010 was caused by the anthropogenic increase in greenhouse gas concentrations and other anthropogenic forcings together" (IPCC, 2013). Since AR5, evidence supporting human influence contributing to the global mean temperature rise has continued to accumulate. Canty et al. (2013) used an energy balance model for attribution and inferred that anthropogenic forcing has contributed significantly to the global mean temperature rise since the 1880s. Based on Granger causality tests, Stern and Kaufmann (2014) pointed out that human activity contributes partially to the observed global temperature rise. In addition, Ribes et al. (2017) proposed a new method for detection and attribution that uses additive decomposition and hypothesis testing, and they obtained consistent conclusions with AR5.

From the perspective of spatial scale, detection and attribution at continental and smaller scales are more complicated than at the global scale (Hegerl et al., 2007; Stott et al., 2010; Bindoff et al., 2013). The difficulty for regional detection and attribution lies in several areas: the larger relative contribution of internal variability at the regional scale; the lower amount of spatial information to help distinguish between the responses to different forcings; the importance of some omitted forcings in global climate model simulations; and the less reliable simulations of forced responses and internal variability (Bindoff et al., 2013). The earliest systematic regional-scale attribution studies focused on mean temperature changes across continents. Zwiers and Zhang (2003) detected the effects of greenhouse gases and sulfate aerosols on temperature changes in six spatial domains from the global to regional scales, such as Eurasia and North America. Using simulations from HadCM3, Stott (2003) investigated the response of changes in continental-scale mean temperature to natural and anthropogenic forcings and concluded that warming effects of anthropogenic greenhouse gases can be detected and separated from natural forcing. In the mid–high latitudes of the Northern Hemisphere, from the hemispheric to subcontinental scales, Qian and Zhang (2015) found that the anthropogenic effect on winter and summer temperatures can be detected and separated from natural forcing. Signals of human influence in mean temperature changes at continental and subcontinental scales have also been detected in some other studies (Karoly et al., 2003; Zhang et al., 2006; Jones et al., 2013). Although the Antarctic region was warming during 1950–2008, due to the uncertainties in observations in this region, AR5 reported low confidence that the increase in average temperature at the limited sites in the Antarctic region can be attributed to human activities (Gillett et al., 2008; Bindoff et al., 2013; Jones et al., 2013).

Attribution research on temperature changes at continental and smaller scales is still advancing, results of which further strengthen and improve previous research. Knutson et al. (2013) demonstrated that, as with continental regions, such as Europe, Africa, Asia, Australia, and South America, the contribution of human activities to temperature changes in the oceanic basins, except North Atlantic, is also detectable. Distinct from previous work that attributed Arctic warming to the combined effects of greenhouse gases and other anthropogenic forcings (Gillett et al., 2008), Najafi at al. (2015) separated and quantified the contributions of greenhouse gases, other anthropogenic forcers (dominated by aerosols), and natural forcing to observed Arctic temperature changes. They found that, although the increase in greenhouse gas concentrations contributed to the observed warming of the Arctic in the past century, approximately 60% of the warming induced by greenhouses gases was offset by the combined response to other anthropogenic forcings. Sun et al. (2014) stated that the CMIP5 multi-model average shows high skill in simulating the change of average temperature in eastern China under the combined anthropogenic and natural forcings, and human activities are responsible for the warming after the 1980s in this region because the warming does not occur when simulations include only the natural forcing. Sun et al. (2016a) revealed that the annual average temperature rise over China could be attributed to the increase in greenhouse gas concentrations, and the warming in China brought by urbanization accounts for about 1/3 of the total mean temperature increase. In detection and attribution research on annual mean temperature change in western China, Wang Y. J. at al. (2018) found that anthropogenic warming could explain most of the temperature rise in this region. Considering the uncertainty brought by model imperfections in describing the multidecadal internal variability at the regional scale, Qian (2016a) used the observed temperature series of eastern China in the past 100 years and an adaptive signal processing technology to separate the multidecadal variability. It was found that the multidecadal variability enhances the warming of the early 20th century and contributes to about 1/3 of the warming of the past 30 years. This conclusion further verifies previous findings about the major role that human activities play in climate change. Wan et al. (2018) found that the observed annual mean temperature across Canada increased by 1.7°C (90% confidence interval [1.1°, 2.2°C]) between 1948 and 2012, a large part of which can only be explained by the effects of external forcing on the climate. It was estimated that the human influence contributes 1.0°C [0.6°, 1.5°C] to the observed warming, while natural forcing only contributes 0.2°C [0.1°, 0.3°C].

The attribution of temperature change at smaller scales, such as the model grid scale, has also been involved in some research (Karoly and Wu, 2005; Mahlstein et al., 2012; Jones et al., 2013). However, since climate models usually lack the process of simulating regional details, and the uncertainty of observation is relatively larger at this small scale, it is still difficult to obtain confident attribution results (Hegerl et al., 2007; Stott et al., 2010). Moreover, Hegerl et al. (2007) pointed out that attribution analysis at this grid scale is essentially a global-scale study, because the interpretation of its results still depends on statistics at global scales.

3.2 *Precipitation*

Understanding how human-induced climate change affects precipitation around the world is also important for defining mitigation policies and adaptation planning (Sarojini et al., 2016). However, due to the limited length, sparse spatial coverage, and quality problems of precipitation observational records, as well as the difficulty for models to accurately simulate precipitation and the considerable impact of internal variability, the attribution of changes in precipitation is far more complicated than that of temperature (Sarojini et al., 2012, 2016; Bindoff et al., 2013; Wan et al., 2013). Zhang et al. (2007) argued that the failure of previous attribution studies with respect to precipitation changes at the global scale was partly because precipitation changes in different regions offset each other and reduce the amplitude of the global average signals. They found that global precipitation was redistributed across latitudes both for observation and the model simulation, reflected by increased precipitation in the midlatitudes of the Northern Hemisphere, decreased precipitation in the subtropical and tropical regions of the Northern Hemisphere, and a wetting trend in the subtropical and tropical regions of the Southern Hemisphere over part of the 20th century.

Regarding changes in the latitudinal pattern of large-scale precipitation change, Zhang et al. (2007) found that human influence is detectable and attributable. In addition, for the zonally averaged pattern, anthropogenic influence has also been detected in annual precipitation at high latitudes and seasonal precipitation in the Northern Hemisphere (Min et al., 2008; Noake et al., 2012; Polson et al., 2013). Similarly, changes in the pattern of annual and seasonal precipitation over oceanic areas can also be partly attributed to human influence (Terray et al., 2012; Marvel and Bonfils, 2013). Using improved observation data and the latest CMIP5 model data, Wan et al. (2014) found that anthropogenic forcing could be separated from natural forcing for the average precipitation in mid–high latitudes of the Northern Hemisphere, although natural forcing signals are difficult to detect robustly. Their study further verifies previous attribution conclusions on precipitation change at high latitudes (Min et al., 2008).

Delworth and Zeng (2014) stated that many aspects of the observed average rainfall decline in southern and southwestern Australia can be simulated in response to human-induced changes in atmospheric greenhouse gases and ozone levels, whereas anthropogenic aerosols did not reduce the precipitation in the simulation. Liu et al. (2015) and Ma et al. (2017) reported that precipitation in eastern China shows a significant shift from light to heavy precipitation. The former study attributed this change to global warming. The latter one analyzed the responses of precipitation to different forcings in detail and found that anthropogenic forcing, including greenhouse gas forcing, had a detectable contribution to the increasing shift toward heavy precipitation over eastern China. Burke and Stott (2017) analyzed the impact of human-induced climate change on precipitation brought by the East Asian summer monsoon. Their results showed that human influence has led to an overall reduction in total monsoon precipitation over the past 65 years, and an increase in dry days in eastern China. Zhang (2015) reviewed recent progress in the diagnosis and attribution of summer monsoon precipitation over eastern China. The review stated that the intensity of the East Asian summer monsoon and summer precipitation in eastern China does not show any trend, and their relationship to rising temperatures remains unclear. Compared with natural forcing, the extent to which the East Asian climate is affected by anthropogenic factors remains controversial.

Furthermore, it is noteworthy that the precipitation changes are affected not only by anthropogenic greenhouse gases, but also by aerosol forcing. Polson et al. (2014) discovered that anthropogenic aerosol, rather than human-induced greenhouse gas concentrations or natural forcing, is the dominant factor driving changes in monsoonal precipitation in the Northern Hemisphere over the second half of the 20th century. Despite the accumulating evidence for human influence on global patterns of precipitation, the attribution of regional-scale precipitation changes is still challenging. Sarojini et al. (2016) believed that deepening our understanding of the physical processes of human activities affecting precipitation changes, developing innovative detection and attribution methodologies, and using novel methods of confronting models with observations, can all lead to progress and development in the attribution of regional precipitation changes.

3.3 *Atmospheric circulation*

There is increasing evidence for effects of stratospheric ozone depletion and increasing greenhouse gas concentrations on tropical circulation, the poleward expansion of the Hadley circulation, and the positive trend of the Northern Annular Mode and Southern Annular Mode (NAM and SAM) since the middle of the 20th century (Hu and Tung, 2003; Hu et al., 2011; Bindoff et al., 2013). The latest research in this area also finds similar effects of the major types of anthropogenic forcing on these changes in atmospheric circulation.

A recent study by Allen et al. (2014) pointed out that anthropogenic aerosols contribute to the width of the tropical belt through modifying the Pacific Decadal Oscillation (PDO). They concluded that tropical expansion and contraction are regulated by multidecadal SST variability, which is related to the PDO and anthropogenic aerosols. In terms of weakening tropical circulation, He and Soden (2015) reported that mean SST warming is more dominant than direct CO_2 forcing. However, in terms of the spatial distribution of weakening tropical circulation, direct CO_2 forcing, mean SST warming, and changes in the SST pattern all play an important role, especially in the ocean. A simulation study carried out by Tao et al. (2016) using the CMIP5 models demonstrated that, among the three major types of anthropogenic forcings, the increase in greenhouse gas concentrations and stratospheric ozone depletion would cause the poleward expansion of the Hadley circulation, whereas anthropogenic aerosols have no significant effect. Kim et al. (2017) also revealed that the poleward expansion trend of the Hadley circulation in the Atlantic and Indian oceans might be attributable to stratospheric ozone depletion. Moreover, some studies have also confirmed that the observed positive trend of SAM index is very likely due to human-induced stratospheric ozone depletion and increased greenhouse gas concentrations (Lee and Feldstein, 2013; Abram et al., 2014).

Currently, some studies are performing attribution from the perspective of dynamic factors, using related atmospheric circulation to assess the anthropogenic influence on regional climate and climate variables or phenomena (precipitation, sea ice, etc.) that are difficult to simulate. Gillett et al. (2003) found that a climate model significantly underestimated the response of sea level pressure to climate change, thereby underestimating the increasing trend of the North Atlantic Oscillation index in the context of global warming, further leading to an underestimation of the impacts of the anthropogenic influence on European climate. In subsequent studies, they found the combined anthropogenic influence on the changes in sea level pressure to be detectable and separated it from the responses to natural forcing (Gillett and Stott, 2009). Furthermore, they reported that changes in greenhouse gases, aerosols, and ozone levels have all contributed significantly to the trends in sea level pressure over the past 60 years, but with distinguishable contributions. These results help us to understand historical changes in atmospheric circulation and have the potential to help improve the projection of circulation changes (Gillett et al., 2013).

Due to the limitations of precipitation observations, attribution results with respect to precipitation changes can alternatively be indirectly evidenced by their consistency with attribution conclusions related to large-scale sea level pressure changes (Bindoff et al., 2013). Based on observations and reanalysis data, Haumann et al. (2014) revealed that, on the multidecadal timescale, the variation of Antarctic sea ice is related to the intensification of meridional winds caused by the zonally asymmetric decrease in high-latitude surface pressure. In their simulations, this lowering of surface pressure was driven by the combination of stratospheric ozone depletion and increased greenhouse gas concentrations. Combining these two arguments, they inferred that human-induced climate change had had a possible influence on the observed changes in Antarctic sea ice. In terms of the decline in Arctic sea ice, Ding et al. (2017) presented evidence that internal variability dominates the trend of Arctic summer circulation and may contribute to about 30%–50% of the overall reduction in September sea ice since 1979. The changes in atmospheric circulation and the mode of the variability are critical to regional climate and its variability, as changes in the circulation can reinforce or offset the effects of external forcing on the local climate.

In summary, the latest attribution studies have accumulated further evidence of the role of human activities in some circulation-related phenomena and modes of variability, such as tropical circulation, the NAM, SAM, and sea level pressure. However, for other circulation-related climate phenomena, such as El Niño, the Indian Ocean dipole, PDO, and the monsoons, due to large uncertainties in observations and model simulations, confidence regarding attribution results for these phenomena remains low.

4. Attribution of long-term changes in climate extremes

The most easily perceived impact of climate change is the change in extreme precipitation or other weather extremes and short-term climate events, which have a tremendous influence on society, economy, and ecosystems. It is therefore important to determine whether these extreme events have changed and whether they can be attributed to anthropogenic forcing (Barnett et al., 2005). The IPCC Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation (SREX) conducted a detailed assessment of the causes of changes in various extreme events, but did not include attribution analyses of regional-scale extreme events (Seneviratne et al., 2012). AR5 complemented and improved the attribution of extreme events based on AR4 and SREX. Attribution analyses on changes in extreme events also focused on the contribution of human influence to the detected trends (Seneviratne et al., 2012; Bindoff et al., 2013).

Recent detection and attribution studies have further identified and evidenced the impact of anthropogenic and/or natural forcing on observed changes in extreme temperature. Fischer and Knutti (2015) argued that in the context of a present-day global mean temperature rise of about 0.85°C, 75% of moderate daily hot extremes can be attributed to the observed post-industrial warming, which is in turn primarily caused by human influence. Based on the Hadley Centre Global Climate Extremes Index 2 (HadEX2) observations and CMIP5 model simulations, attribution results from Kim et al. (2015) confirmed previous HadEX/CMIP3-based results. In terms of the increase in global mean and regional (northern continental) means of four indices of extreme temperatures, signals of human influence were robustly detected and clearly separable from the response to natural forcing. In addition, they discovered that the attribution results show general insensitivity to different model samples and different data availability used to implement the attribution analyses. Wang et al. (2017) introduced generalized extreme theory into the optimal fingerprinting method and used the coordinate descent algorithm to estimate the scaling factor by maximizing the independence likelihood, which surpassed Zwiers et al. (2011) in terms of computational efficiency and accuracy. Based on this methodology, they presented attribution analyses on the extreme temperatures in 17 subcontinental regions over the period 1951–2010. It was revealed that anthropogenic signals could be clearly separated from natural forcing in about 4–6 regions. From the perspective of return level, the average waiting times for the temperature of the coldest night and day had increased, while the average return period for the temperature of the warmest night and day had shortened in most of the selected regions.

Studies have also provided evidence that human activities facilitated the increase in the frequency of hot summers in the Northern Hemisphere in the second half of the 20th century (Kamae et al., 2014; Christidis et al. 2015). Through detection and attribution of a heat wave index, Knutson and Ploshay (2016) pointed out that anthropogenic influence had contributed to the increase in the magnitude of summer heat stress both at the global scale and in most land areas since 1973. Li C. et al., (2017) used wet bulb globe temperature (WBGT) as a measure of the environmental conditions favoring heat waves, revealing that anthropogenic forcing had substantially increased the likelihood of extreme summer-mean WBGT in the land regions of the Northern Hemisphere. It was estimated that the probability of summer-mean WBGT exceeding the observed historical record had increased by a factor of at least 70 times.

In attribution studies of changes in temperature extremes defined by the percentile method and annual maxima of daily maximum and minimum temperatures in China by Lu et al. (2016) and Yin et al. (2017), signals of anthropogenic forcing were robustly detected in both cases. Dong et al. (2018) applied a variety of extreme temperature indices to attribute the frequency and intensity of extreme temperatures in the Asian region, and further compared the similarities and differences between the attribution results of different indices. They found that anthropogenic signals can be clearly separated from natural forcing in changes of almost all indices, indicating the robustness of the conclusion that the warming signal can be attributed to external forcing. Wang J. et al. (2018) explored the possibility of human influence on the frequencies of four threshold-based extreme temperature indices (summer days, tropical nights, icy days, and frosty nights) in eastern China over the period 1962–2010. Their results showed detectable anthropogenic influence in the observed changes in the frequency of the above-mentioned four extreme temperature indices, and the effects of increased greenhouse gas concentrations changed the frequency of summer days (tropical nights, icy days, and frosty nights) by 3.48 ± 1.45 (2.99 ± 1.35, -2.52 ± 1.28, and -4.11 ± 1.48) days decade^{-1}.

In rapidly developing regions such as China, some attribution analyses have claimed effects of urbanization on changes in extreme temperature. For example, a significant urbanization effect (external forcing of land-use change) on changes in the extreme high temperature in Shanghai was detected by Qian (2016b) through contrasting urban and rural stations, contributing up to 1/3 to the trend of the heat wave index of interest. Ren and Zhou (2014) also assessed the impact of urbanization on extreme temperature changes in China over the period 1961–2008. They demonstrated that, for the country as a whole, the annual-mean urbanization effect on the daily minimum, maximum, and mean temperature was statistically significant. The above findings further strengthen the conclusion reached in AR5 that it is very likely that human influence has contributed to the change in frequency and intensity of temperature extremes.

Global warming exacerbates the water cycle, and the increase in extreme precipitation seems to be relatively faster than the increase in average precipitation per degree of warming (Allen and Ingram, 2002). Although the attribution of extreme precipitation poses challenges to researchers, considering the low signal-to-noise ratio that results from uncertainties in observational data and model simulations and the large natural variability, some progress has been made recently. Min et al. (2011) applied optimal fingerprinting methods to conduct attribution of changes in annual maxima of daily (RX1D) and five-day consecutive (RX5D) precipitation based on simulations from CMIP3. They discovered that human-induced global warming contributes to the observed intensification of heavy precipitation events over about 2/3 of land areas with available data in the Northern Hemisphere. Based on updated observations and CMIP5 model simulations, Zhang et al. (2013) also found that the effects of anthropogenic forcing could be detected in observed changes in RX1D and RX5D, strengthening the conclusions drawn by Min et al. (2011). In addition, Zhang et al. (2013) stated that the signals of human influence can be detected not only in individually forced changes, but also in changes forced by anthropogenic and natural forcings combined. Fischer and Knutti (2015) reported that, under present-day climate conditions, about 18% of moderate daily precipitation extremes could be attributed to climate warming since pre-industrial times. As the warming continues, the contribution of anthropogenic influence to the increase of extreme precipitation will get larger.

Attribution results for extreme precipitation over India from Mondal and Mujumdar (2015) indicated that, at the 95% confidence level, human influence could be detected in the changes in RX5D, but not in the changes in RX1D. Chen and Sun (2017) argued that human influence was responsible for the nearly 13% mean increase in the frequency of daily extreme precipitation in China in recent decades. They also found an amplification of extreme precipitation with further warming, which is consistent with Fischer and Knutti (2015). Gao et al. (2018) found that natural variability contributes more to the mean state of extreme precipitation, and anthropogenic influence caused greater variability of extreme precipitation in 1986–2012 than in 1960–85 in the coastal region of southeastern China.

For drought, an extreme climate phenomenon affected by many factors, such as precipitation, temperature, wind speed, and soil moisture, detection and attribution at the global scale are highly uncertain (Seneviratne et al., 2012; Bindoff et al., 2013). Due to the use of different indices or various observational and model data, the detection results for observed changes in drought can even be conflicting, and results for drought-related attribution are relatively sparse (Sheffield et al., 2012; Dai, 2013; IPCC, 2013). In view of the historical evidence of high-magnitude natural drought and flooding reconstructed from paleoclimatic records, the recent long-term drought in western North America does not fall definitely outside the range of natural variability of precipitation in the region (Cayan et al., 2010; Seager et al., 2010). For the drought trend in North China, Qian and Zhou (2014) revealed that the multidecadal variability associated with PDO phase transition is the dominant factor.

To sum up, there is sufficient evidence to support that anthropogenic forcing has had an impact on long-term changes in temperature extremes. So far, at global, continental, and subcontinental scales, attribution studies on changes in temperature extremes have been able to separate and quantify the relative contributions of anthropogenic and natural forcing. Post-AR5 attribution studies on changes in temperature extremes further enrich the evidence for anthropogenic influence on temperature extremes, and enhance the robustness of the conclusions made in AR5. A substantial body of research suggests that extreme precipitation is showing an expected increase under human influence, but direct evidence of anthropogenic influence on changes in extreme precipitation is still limited. Therefore, given the limited data coverage, poor model performance, and low signal-to-noise ratio, there is only a moderate level of confidence for attributing changes in extreme precipitation to anthropogenic forcing at the global scale. Moreover, at smaller spatial scales, the attribution of changes in extreme precipitation is more challenging. There are still large uncertainties in the detection of changes in drought at large or global scales because the indices and observations used are not unified. It is difficult to distinguish the decadal scale variability from the long-term changes in drought, so the confidence of the relevant attributions of drought changes in land regions at the global scale is low.

5. Attribution of extreme weather and climate events

The attribution of extreme weather and climate events is closely related to disaster risk perception and reduction, climate change adaptation, and communication and decision-making. It is a very important part of climate change attribution studies (NAS, 2016). In the past decade, extreme event attribution has developed rapidly. After Stott et al. (2004) presented initial analyses of the relationship between climate change and the European heat wave, attribution studies for different types of extreme events have emerged, such as heat waves, droughts, extreme precipitation, and even thunderstorms, tropical cyclones, and haze (Herring et al., 2016, 2018; Li et al., 2018). BAMS has published six editions of its annual special issue on extreme event attribution, in which information on the types, occurrence locations, and impacts of extreme events (thus far, during 2011–16) has become richer. According to statistics, the number of event attribution studies published each year in this special issue has grown from 6 to a current quantity of around 30, and a total of 131 research papers have been published in the six years thus far (Herring et al., 2018). The rise of event attribution research not only promotes an in-depth understanding of the physical mechanisms that cause changes in extreme events, but also facilitates the rapid development of methods for event attribution (Stott et al., 2016). The complement of newly developed methods has enhanced the confidence in event attribution results and paved the way for answering questions about the causes of extreme events raised by stakeholders and the public in the immediate aftermath of such events.

In order to better assess the risks associated with extreme weather and climate events, event attribution studies focus on quantifying the extent to which anthropogenic and natural forcing alter the probability and intensity of a particular type of extreme events (Stott et al., 2016; Knutson et al., 2017). For any extreme event, the results of the attribution study hinge on how to frame the scientific problem of the attribution of the extreme event, and on the choice of attribution methods, the data, the model, and statistical tools selected (NAS, 2016). Firstly, framing of the event attribution questions, which consists of how and in which context the questions are posed, is a key issue for designing and conducting event attribution studies and communicating results (Trenberth, 2012; Otto et al., 2013, 2015; Trenberth et al., 2015). Secondly, different attribution methods may result in distinct or even conflicting attribution results, whereas different methods leading to similar attribution results can enhance the confidence in extreme event attribution conclusions (NAS, 2016; Stott et al., 2016). Furthermore, the performance of climate models in simulating extreme events and the systematic error of thermal feedback are sources of uncertainty for event attribution studies that use climate models (Stott et al., 2016; Sippel et al., 2017; Vogel et al., 2017). Lastly, since the dominant circulation during extreme events also plays an important role in the occurrence and maintenance of extreme events, the uncertainty with respect to the internal variability of the circulation and the influence of climate change on the circulation also brings interference to the detection of anthropogenic signals in extreme events (Shepherd, 2014; Stott et al., 2016; Mitchell et al., 2017). In a word, uncertainties in attribution studies of extreme events are worth noting. In order to achieve a clear and unambiguous interpretation of event attribution studies, the assumptions and choices made in the process of the study need to be clearly stated, and uncertainties soundly estimated (NAS, 2016). The NAS report in 2016 concluded that confidence is higher for extreme events that relate to temperature, such as heat waves and cold waves (Fig. 3). Due to the regional variability of precipitation and the complexity of land-surface feedback to drought, only medium confidence can be achieved in the attribution of extreme precipitation and drought events, which is slightly lower than that of temperature extremes. In comparison, the attribution of other extreme events, such as hurricanes and severe convective storms, is much more complicated. Attribution of these events requires extremely high-resolution simulations, and thus there is less confidence in the attribution results for extreme events of this nature.

For temperature-related extreme events, such as hot days, heat waves, cold days, and cold waves, most attribution studies have found that human influence has changed the frequency or magnitude of these extreme temperature events based on model simulations (Stott et al., 2004; Christidis et al., 2014; Min et al., 2014; Christidis and Stott, 2015; Perkins and Gibson, 2015; Song et al., 2015; Sun et al., 2016b; Herring et al., 2018). In addition to the use of climate models, studies using analogue-based methods have found that winters in Europe became anomalously warmer than the temperatures controlled by similar circulations in previous decades, and

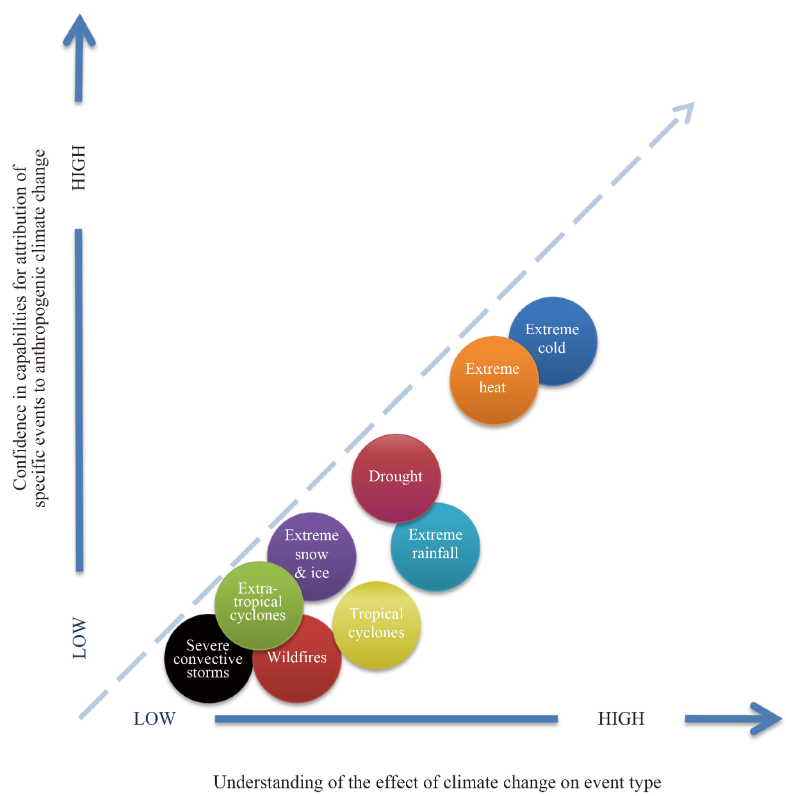

Fig. 3. Schematic depiction of the NAS report in 2016 assessing the state of attribution science for different event types. The horizontal position of each event type reflects an assessment of the level of understanding of the effect of climate change on the event type, while the vertical position of each event type indicates an assessment of scientific confidence in current capabilities for the attribution of specific events to anthropogenic climate change for that event type (Source: NAS, 2016).

infer that this might be caused by thermal factors (Yiou et al., 2007; Cattiaux et al., 2009, 2010). Uhe et al. (2016) applied a variety of methods to conduct attribution analysis of heat waves in Europe in 2014, and found a strong anthropogenic signal too. Sun et al. (2014, 2016b) and Ma et al. (2017) stated that human influence substantially increased the likelihood of heat wave occurrence in western China in 2015 and in central–eastern China in 2013. The 2016 edition of BAMS special issue explaining extreme events reported that up to 28 of the 29 attribution studies on temperature extremes found a detectable imprint of human influence (Herring et al., 2016). The latest issue of this report published several new attribution studies on extreme temperature events that have drawn novel and significant conclusions. Imada et al. (2018) and Knutson et al. (2018) concluded that the record-heat occurring globally and in Asia in 2016 was not possible without anthropogenic influence. Moreover, based on CMIP5 model simulations, Walsh et al. (2018) stated that no analogous instances could be found in the pre-industrial climate for the anomalies in ocean water off the coast of Alaska in 2016. The best-estimated fraction attributable risks obtained by the above three studies are all 1, which means that these heat events were not possible in a "counterfactual" world without human influence. In short, numerous studies have confirmed a strong impact of human-induced climate change on temperature extremes, as evidenced by extreme hot events becoming more frequent and intense. As for extreme cold events, it has been revealed by several studies, including the attribution of record-breaking cold events in eastern China in January 2016 (Qian et al., 2018; Sun et al., 2018), that human influence has reduced the probability of occurrence of these events.

There is also an increasing number of studies focusing on the attribution of extreme precipitation (King et al., 2013; Singh et al., 2014; Schaller et al., 2016) and drought (King et al., 2014; Diffenbaugh et al., 2015; Williams et al., 2015). Figure 4 is a schematic representation of the results of an attribution study on an extreme precipitation event, which characterizes the human influence on the changes in the frequency and intensity of this extreme precipitation event. This attribution study was conducted for a persistent extreme precipitation event in the United States in August 2016 and the results showed that human influence led to a 40% increase in the frequency of a similar extreme precipitation event and a 10% increase in the maximum three-day total precipitation (van der Wiel et al., 2016).

Attribution analyses carried out by Burke et al. (2016) on heavy precipitation in southern China in 2015 indicated that anthropogenic factors dominated the increase in the risk of such events. Precipitation has high spatial variability, which results in the sensitivity of extreme precipitation attribution to the selection of the study region. For example, for two subregions in the lower reaches of the Yangtze River, Li C. X. et al. (2017) revealed that anthropogenic influences likely contributed to increasing the probability of extreme precipitation events like that in May 2016 in the northern subregion, whereas it was opposite for the southern subregion. Recent studies (Sun and Miao, 2018; Yuan et al., 2018; Zhou et al., 2018) on extreme precipitation in China in 2016 took into account the combined effects of El Niño and anthropogenic forcing and revealed that the contribution to the increase in the intensity of extreme precipitation in eastern China from anthropogenic forcing could still be detected even though the El Niño signal was separated. Besides, there are also many studies that did not find any human influence on precipitation extremes (Herring et al., 2016).

Because of the complex mechanism leading to the occurrence of drought, and the need to accurately understand the land–atmosphere feedback involved, the attri-

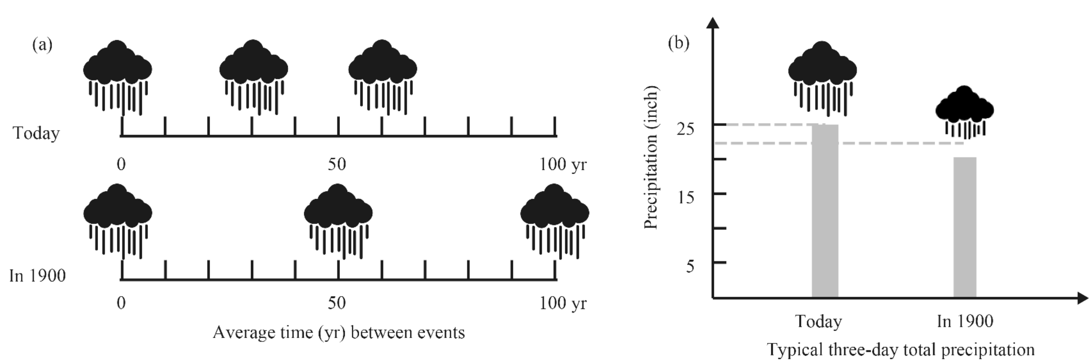

Fig. 4. Influence of anthropogenic climate change on (a) the average return time and (b) intensity of typical three-day total precipitation [drawn based on the results of van der Wiel et al. (2016)].

bution of drought events still faces challenges (Dai, 2011; Seneviratne et al., 2012). Considering the difficulty of direct attribution, several studies have conducted attribution analyses of precipitation extremes and droughts from the perspective of the dominant circulation, also finding human influence to be responsible for changes in these events (Yiou and Cattiaux, 2014; Christidis and Stott, 2015; Harrington et al., 2016). In addition, many kinds of other extreme events or phenomena have aroused the interest of scientists in the climate attribution field, such as tropical cyclones, wildfires, storms, and so on. However, attribution results for such extreme events still involve considerable uncertainty (Herring et al., 2014; NAS, 2016). Among them, one interesting study conducted by Li et al. (2018) showed that anthropogenic forcing had increased the probability of haze-favorable atmospheric circulations in eastern China. It was estimated that human influence had caused the likelihood of the atmospheric pattern conducive to severe haze to increase by at least 45% in January 2013 and 27% in December 2015.

In addition, some attribution studies on extreme events have begun to focus on separating the effects of human influence on changes in dynamic factors (such as large-scale circulation) and thermodynamic factors (such as air temperature or SST), and quantifying the contributions of human-induced dynamic and thermodynamic factors to the changes in the probability or intensity of extreme events (Wu and Karoly, 2007; Schaller et al., 2016; Vautard et al., 2016). For example, Vautard et al. (2016) used flow analogs across two datasets of model simulations representing the “counterfactual” and “factual” climate to quantitatively estimate each contribution to the changes in the occurrence probability of the extreme event under investigation. When applying this method to extreme January precipitation in southern UK, they demonstrated that atmospheric flow changes contributed to about 1/3 of the increase in the January precipitation amount, and the other 2/3 could be explained by thermodynamic changes. This result also indicates that, for the human-induced changes in the intensity of this extreme precipitation event, the effect of thermodynamic changes was greater than that of the dynamic factor. Undoubtedly, this method can be generalized to many other types of extreme events and regions. For changes in different kinds of extreme events caused by changes in external forcing, the relative contributions from dynamic and thermodynamic factors may vary greatly. The emergence of these studies is beneficial for deepening our understanding of the dynamic and thermodynamic contributions to human-induced changes in extreme events.

6. Discussion and future research directions

Climate change attribution mainly includes the attribution of trends or long-term changes in climate variables and extreme events, the attribution of extreme weather and climate events, and the attribution of climate change impacts. This paper reviews the latest research progress in climate change attribution, focusing on the long-term changes of temperature, precipitation, circulation, and extreme events and event attribution studies.

To date, attribution studies on changes in mean temperature at global and regional scales have accumulated a chain of evidence demonstrating that long-term changes in temperature in the 20th century are attributable to anthropogenic influence. AR5 reported that it is extremely likely that more than half of the observed increase in global average surface temperature from 1951 to 2010 was caused by the anthropogenic increase in greenhouse gas concentrations along with other anthropogenic forcings. Numerous studies have used newly developed methods, updated data, and new climate models to further confirm the robustness of the attribution conclusions about the changes in mean temperature drawn in AR5. Although the human influence on mean temperature changes is already unambiguous, the global temperature change since 1951 attributable to anthropogenic forcing continues to be uncertain, largely a result of the considerable uncertainty in the estimated total radiative forcing due to aerosols. It is technically challenging for attribution studies to separately quantify the contributions of greenhouse gases and aerosols to temperature changes (Bindoff et al., 2013; Knutson et al., 2017).

Due to the limited coverage of observations, the challenges in precipitation modeling, and the large natural variability, the attribution of trends or long-term changes in precipitation is much more complicated than that related to temperature (Sarojini et al., 2012; Bindoff et al., 2013; Wan et al., 2013). Based on improved observations and model data, signals of human influence have been detected in annual and seasonal precipitation patterns in global land and sea areas (Zhang et al., 2007; Min et al., 2008; Noake et al., 2012; Terray et al. 2012; Marvel and Bonfils, 2013; Polson et al., 2013; Wan et al., 2014). For the attribution of regional precipitation changes, studies have found imprints of human-induced climate change in rainfall declines in southern and southwestern Australia, and in shifting toward heavy precipitation and a reduction in the decline of total monsoonal rainfall in eastern China (Delworth et al., 2014; Liu at al., 2015; Burke and Stott, 2017; Ma et al., 2017). However, progress on the attribution of changes in regional precipitation is still lacking. Due to the considerable uncertainty involved in modeling and observations, compelling evidence of an anthropogenic fingerprint on regional precipitation can be obscured (Sarojini et al., 2016). Quantifying how human activities affect regional water cycles requires the consideration of introducing new methods that take full advantage of our physical expectations to identify the different effects of natural and anthropogenic influence on precipitation. Innovative statistical methods and the development of high-quality observations and high-resolution models will contribute to future progress in the attribution of regional precipitation changes (Sarojini et al., 2016).

Changes in atmospheric circulation and modes of variability are critical to regional climate and its variability, because changes in circulation can enhance or offset the effects of external forcing on local climate. There is an increasing body of evidence presented in recent attribution studies showing that the anthropogenic influence is detectable in the changes in some circulation-related phenomena and modes of variability, such as tropical circulation, the NAM, the SAM, and sea level pressure (Gillett and Fyfe, 2013; Abram et al., 2014; Allen et al., 2014; He and Soden, 2015; Tao et al., 2016; Kim et al., 2017). However, for other circulation-related phenomena with large observational and modeling uncertainties, such as El Niño, the Indian Ocean dipole, and the monsoons, attributing changes for these phenomena to human influence remains unreliable. From the perspective of related circulation patterns, some studies have indirectly demonstrated the anthropogenic influence on the long-term changes of some climate variables (e.g., precipitation, sea ice) or phenomena that are difficult to accurately simulate (Haumann et al., 2014; Ding et al., 2017).

Following the release of AR5, attribution results with respect to global and regional changes in temperature extremes have further enriched the evidence of anthropogenic influence and strengthened the robustness of the conclusions drawn in that report (Fischer and Knutti, 2015; Kim et al., 2015; Knutson et al., 2016; Lu et al., 2016; Li C. et al., 2017; Wang et al., 2017; Yin et al., 2017; Wang J. et al., 2018). Current attribution studies are able to quantitatively separate the contributions from anthropogenic and natural influence on changes in temperature extremes at global, continental, and subcontinental scales. In addition, the contributions of other external forcings, such as urbanization, to changes in extreme temperature have also been explored and quantified (Ren and Zhou, 2014; Qian, 2016b). In the face of sparse data coverage, challenges in modeling, and low signal-to-noise ratios, direct evidence of human-induced climate change affecting changes in extreme precipitation remains limited. Also, only medium confidence can be obtained when attributing changes in global-scale precipitation extremes to anthropogenic influence (Bindoff et al., 2013; Zhang et al., 2013; Fischer and Knutti, 2015; Mondal and Mujumdar, 2015). Moreover, the attribution of changes in precipitation extremes at smaller spatial scales poses an even greater challenge (Bindoff et al., 2013). Due to the different indices and observational data used, large uncertainties still exist with respect to the detected signals of drought phenomena on large or global scales, resulting in less reliable attributions of drought changes in the global terrestrial region. Due to the disunity of drought indices and observational data used in various studies, large uncertainty arises in the detected signals of changes in drought at the global scale or in large regions, which further results in low confidence regarding attribution results for droughts in global land areas (Sheffield et al., 2012; Dai, 2013; IPCC, 2013).

The attribution of extreme weather and climate events is currently in a stage of rapid development, with related findings providing new insights into the effects of anthropogenic climate change on the frequency or magnitude of specific extreme weather events, favorable for risk management and adaptation planning (NAS, 2016). Of the 131 papers in BAMS special issues explaining extreme events published over the past six years, approximately 65% found anthropogenic effects on extreme events, with the remaining 35% unable to identify a discernable role for climate change. In terms of the confidence in event attribution, the highest levels are achieved for extreme events linked to temperature, followed by extreme precipitation and then drought events. For smaller-scale extreme events, the difficulty in accurately modeling them leads to low confidence in the attribution results obtained. Some of the latest research has begun to quantify the relative contributions of anthropogenic dynamic and thermodynamic factors to changes in the probability and intensity of an extreme event, thereby deepening our understanding of the role that dynamic and thermodynamic factors play in climate change due to external forcing.

Although extreme event attribution research has made considerable progress recently, the geographical coverage of events remains patchy, and the types of extreme events covered is insufficiently diverse. Those areas that have received relatively less attention but are nonetheless highly vulnerable, as well as some of the more complicated extreme events, deserve more exploration (Stott et al., 2016). The subjectivity involved in selecting the type of extreme event or study region causes a systematic bias called "selection bias." In event attribution studies, the selection bias arising from different sources is almost inevitable. The potential forms of selection bias include: bias from only studying events that have already occurred (occurrence bias); bias from choosing to study events for which the researcher suspects that there is either a detectable human influence in general, or likelihood of an alteration by anthropogenic influence specifically (choice bias); bias from only publishing studies that find an imprint of human influence, either in general or in changes of the likelihood of the events (publication bias); and bias in selecting study regions or event definitions of interest to the researcher (type bias). These selection biases collectively interfere with the ability to draw general conclusions from the numerous studies on the human influence on extreme events. It would therefore be beneficial to develop a set of pre-determined and objective extreme event selection and definition criteria, which can help minimize the selection bias and lead to methodological improvements in some cases (NAS, 2016). There are still considerable uncertainties in the attribution of extreme events, such as for droughts and severe convective storms, and NAS (2016) suggests that attribution for these types of extreme events can be improved by developing transparent, uniform standards within the research field.

As the capability to attribute extreme events increases, the resultant findings can further inform the assessment and management of risks and the development of climate adaptation strategies. In order to provide the large number of decision makers and stakeholders with rigorous and timely assessments of the climate change impact on changes in extreme events, the development of operational attribution systems is essential. A Europe-based research project called EUCLEIA (European Climate and Weather Events: Interpretation and Attribution) has embarked on the development of such an operational attribution system, the aim being to provide timely attribution assessments for newly emerging extreme events based on pre-defined and tested methods and event-selection criteria.

Owing to the relatively late start for attribution studies in China and its special geographical location and complex climate conditions in East Asia, attribution results for climate change in China are relatively scarce. In the past five years, however, attribution research focusing on the whole of China or regions within China have come to the fore. First, in terms of mean temperature changes over China, Sun et al. (2014) conducted detection and attribution for the changes in average temperature in eastern China and found a detectable anthropogenic influence. From the perspective of extreme event attribution, they further quantified the contributions from human influence to the increase in the likelihood of heat waves, like that in summer 2013 in eastern China. Subsequent attribution studies have further analyzed the contribution of urbanization to mean temperature changes over China (Sun et al., 2016a). In addition, attribution research focusing on mean temperature changes in western China has also emerged (Wang Y. J. et al., 2018). Attribution research on long-term changes in regional-mean precipitation change over regions of China has also made some progress (Liu et al., 2015; Burke and Stott, 2017; Ma et al., 2017). For long-term changes in extreme temperature and precipitation in China, existing attribution studies have found that anthropogenic influence has contributed to the trends in both the frequency and intensity of temperature extremes using different indices (Ren and Zhou, 2014; Lu et al., 2016; Qian, 2016b; Yin et al., 2017; Wang J. et al., 2018); furthermore, they have also found that anthropogenic signals can be detected in long-term changes of extreme precipitation (Chen and Sun, 2017; Gao et al., 2018). Event attribution studies for various types of extreme weather and climate events in China are also rapidly accumulating, such as for heat waves (Song et al., 2015; Sun et al., 2016b; Li Y. et al., 2017), heavy precipitation (Burke et al., 2016; Li C. X. et al., 2017), and cold waves (Qian et al., 2018; Sun et al., 2018). These event attribution studies focusing on extreme events occurring in China have revealed that anthropogenic forcing has altered the likelihood of occurrence and magnitude of these extreme events. On the whole, attribution studies on the long-term changes in mean temperature and extreme temperature in China are systematic and fruitful. Such studies have systematically analyzed the effects of human influence on trends in various characteristics of mean temperature and extreme temperature. In addition, event attribution of temperature-related extreme events in regions of China has also strengthened. However, there remains a lack of attribution studies on long-term changes in climate variables and phenomena related to extreme precipitation, drought, and circulation patterns in China. Extreme event attribution for events occurring in China is also lacking from the perspective of some other types of extreme events, such as drought and persistent extreme precipitation. In the future, the development of research in China on climate change attribution will depend on stronger research standards and greater technical support. Moreover, in terms of achieving an in-depth understanding of the underlying mechanisms of anthropogenic or natural climate change in East Asia, improving statistical attribution and model/observation processing methods will help to rapidly improve the capacity of climate change attribution and increase the impact of relevant research results for China (Sun et al., 2013).

Greenhouse gases emitted by human activities will continue to affect humans and natural systems, related to which some types of extreme events are projected to occur more frequently and become more intense (Seneviratne et al., 2012). The risks posed by climate change to human society are not only related to changes in disaster risk, but also closely related to regional exposure and vulnerability. In the face of the same extreme weather and climate events, areas with high vulnerability and exposure will suffer more at the hands of severe meteorological disasters. Thus, society is paying more and more attention to the impact of climate change on humans or natural systems, rather than the changes in climate variables and extreme events. For example, people living in agricultural areas and basins vulnerable to flooding will be more concerned about the risk of flooding than the change in the probability of extreme precipitation. Therefore, in terms of future development, attribution of the impacts of climate change and extreme weather and climate events deserves more attention and development. The attribution of climate change impacts places high demands on the availability and quality of observational data, as the driving factors causing the impacts are highly complex. In addition, the relationship between forcing and its impact remains ambiguous, which poses considerable challenges for impact attribution studies. The impact attribution of extreme weather and climate events has been addressed and highlighted in some studies published in the latest special issue of BAMS explaining extreme events (Herring et al., 2018). However, impact attribution studies still require vigorous development; for instance, including the effects of exposure and vulnerability in addition to meteorological hazard can help achieve a better understanding of the risks brought about by extreme events (Stott et al., 2016). Since detection and attribution rely heavily on model simulations and observations, and the room for improvement with respect to observations is limited, the future development of attribution research depends mainly on improving models and developing new methods. Good news in this respect is that the experimental design and organization of phase 6 of the Coupled Model Intercomparison Project (CMIP6; Eyring et al., 2016) has been put in place. CMIP6 is committed to improving the deficiencies of the climate models in previous intercomparison projects. Moreover, the development or introduction of innovative attribution research methods can not only enrich the results of attribution studies, but also improve the confidence we have in the conclusions reached by such studies. Therefore, assessing and improving climate models, further improving observational data, and developing novel methods will together provide the key that opens the door to exciting future developments in climate change attribution research.

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