

## Invited Review Paper

# Review of recent advances in climate change detection and attribution studies: a large-scale hydroclimatological perspective

P. Sonali and D. Nagesh Kumar

### ABSTRACT

The rapid changes in global average surface temperature have unfathomed influences on human society, environment, ecosystem, availability of food and fresh water. Multiple lines of evidence indicate that warming of the climate system is unequivocal, and human-induced effects are playing an enhanced role in climate change. It is of utmost importance to ascertain the hydroclimatological changes in order to ascertain the characteristics of detection and attribution (D&A) of human-induced anthropogenic influences on recent warming. Climate change D&A are interrelated. Their study enhances our understanding about the rudimentary causes leading to climate changes and hence, considered as a decisive element in all Intergovernmental Panel on Climate Change Assessment Reports. An extensive discussion of the concerned scientific literature on climate change D&A is indispensably needed for the scientific community to assess climate change threats in clear terms. This study has reviewed various processes and advances in climate change D&A analyses at global/regional scales during the past few decades. Regression-based optimal fingerprint approach is majorly employed in climate change D&A studies. The accumulation of inferences presented in this study from numerous studies could be extremely helpful for the scientific community and policymakers as they deal with climate change adaptation and mitigation challenges.

**Key words** | attribution, climate change, climate model, detection, extreme events, fingerprint

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### INTRODUCTION

The '*warming of the climate system is unequivocal*' because of the consistent overall warming trend since the mid 20th century, which can be attributed *extremely likely* to human-induced anthropogenic influence (Stocker *et al.* 2013). The cardinal aim of the Paris agreement is to confine the global warming rate 'well below' 1.5 °C to 2 °C. Since the pre-industrial era the concentration of CO<sub>2</sub> in the atmosphere has increased by about 40% globally. Observed changes in ocean

properties such as sea level, ocean heat content, acidification and salinity are consistent with the changes in the atmosphere due to human-induced anthropogenic effects (Bindoff *et al.* 2013). Extreme event attribution is a recent growing research field which deals with extremes such as heatwaves, droughts, floods and wildfires which vary greatly in different parts of the world. Attributions of these events never conclude concrete inferences, as these compare the probabilities of occurrence of a particular event in the world under the presence/absence of global warming. These help in better analysis of the processes involved, and the inferences can be potential for future policy interaction. Integrated knowledge

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from various streams such as climatology, hydrology and sociology can be useful for event attribution science in analysing the effects of extreme events. However, to date, the science of extreme event attribution is in a nascent stage in most important parts of the globe. Heatwave changes are more rapid under anthropogenic climate change and have calamitous effects on human health (morbidity and mortality rates) and biosphere (Perkins-Kirkpatrick *et al.* 2017). Climate change has affected oceans in different ways, such as ocean atmosphere circulation, ocean acidification and upper ocean warming, which has led to global sea level rise since 1970. There is a reduction in snow cover both at continental and regional scales due to anthropogenic influence. The global water cycle has significantly changed since 1960, which is attributed to human-influenced combined changes in ocean and atmosphere. Global, continental and regional scale intensification of climate extremes have been in evidence since the middle of the 20th century.

There is a need of climate change detection and attribution (D&A) studies as they yield comprehensive knowledge about climate science and help in assessing the causes of recent changes in climate. D&A studies improve our knowledge in assessing the impact of human activities on climate change and help in ascertaining the risks and impacts associated with climate change comprehensively. 'Detection' and 'attribution' are interlinked processes, and challenging because of the associated complex spatio-temporal variations in the atmospheric system and interactions between the natural internal and external (natural and anthropogenic) drivers. A significant gap exists, although this research has been in progress for more than a quarter of a century.

With recent progress in observation, sophisticated climate model simulation and developed methodology, climate change D&A studies have enriched the evidence on human-induced anthropogenic impacts. This paper reviews the recent advances in climate change D&A studies. It also reviews the role of climate models in D&A analysis. Widely adopted climate change D&A methodologies are discussed thoroughly and their suitability for arriving at reliable attribution statements in different spatio-temporal scales are highlighted. The study reviews the evidence depicting human-induced or naturally driven significant changes in different hydroclimatological variables at regional as well as large spatial scales, namely, global,

continental and sub-continental. The effect of human-induced anthropogenic influences, natural internal and external variability on changes in the cryosphere, climate extremes, circulations and oceanic changes are discussed briefly. Extreme events and associated mechanisms with growing interest on event attribution worldwide are focused on specifically. It is difficult to diagnose regional forcings and their responses in the observational record. Hence, there is a high chance of misattributions at regional scales. Hence, special attention is accorded to analyse the regional effects which can have heterogeneous effects across the globe.

### Detection and attribution of climate change

The Intergovernmental Panel on Climate Change (IPCC) was established in 1998 by the World Meteorological Organization (WMO) and the United Nations Environment Programme (UNEP). It presents a comprehensive summary which provides scientific information about the drivers (natural and external) of climate change and impacts and associated risks of climate change. It also helps in developing different adaptation and mitigation strategies which can be helpful in reducing future climate change-related risks. The IPCC has published five comprehensive assessment reports (ARs), respectively, in the years 1990, 1995, 2001, 2007 and 2013. The sixth AR is expected to be completed by the year 2022. Each AR consists of three volumes based on three working groups (WG).

As per IPCC AR5, the process of establishing climate change in a defined statistical sense, without assigning any specific reason is known as detection and the process which assesses the relative contributions of multiple potential causal factors for the detected changes is defined as attribution. These two processes are essential components of all IPCC ARs and substantial progress has been accomplished over the years in different IPCC ARs from 1990 to 2013 (Liu & Xia 2011). Over the years, the confidence level on attribution results has been reported in firmer statistical footing represented as 'likely', 'very likely' and 'extremely likely', respectively, in third, fourth and fifth ARs of the IPCC (Houghton 2001; Solomon *et al.* 2007; Stocker *et al.* 2013). Over the period (from the first to fifth ARs), increasingly confident statements have been reported based on the improved observations, model simulations, climate

forcing estimates and advancement in D&A approaches summarized in Table S1 in the Supplementary Information (Knutson 2017). Accumulation of evidence indicates that human influence has considerably enhanced the probability of occurrence of heatwave events across the globe. Precise prediction of future warming trends at regional scale is difficult compared to that at higher spatial scales. Few existing studies are directed to detect (i.e., distinguish from expected natural internal variability) and attribute (i.e., ascribe a cause to) the observed changes in climate at a regional scale.

It is claimed that global warming has stopped or slowed down. However, studies claim these short-term warming/cooling trends are the result of multi-decadal scale internal variability. Further deep understanding about decadal variability could be beneficial in tracking the energy exchange within the climate system and the role of natural and human-induced external drivers (Zorita *et al.* 2008; Stott *et al.* 2010). Agreement among various studies on the contribution of the Atlantic multi-decadal oscillation (AMO) to global warming is minimal. Hence, internal variability alone cannot result in the observed warming since 1951 (IPCC AR5). The contribution of solar radiation on global warming is lesser compared to greenhouse gases (GHGs) forcing. It has been mentioned that there is a likelihood of warming of the tropospheric temperature since 1961 and cooling of the lower stratosphere since 1971 because of global warming impact. Impact of anthropogenic emission is evident all over the continents except Antarctica. Attribution of tropical cyclone change to anthropogenic influence is low due to inadequate observational evidence and lack of inference about its association with different anthropogenic climate drivers. Robust evidence from multiple studies using various approaches suggests that the major source of changing climate is anthropogenic effects (Bindoff *et al.* 2013).

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## ROLE OF CLIMATE MODELS IN DETECTION AND ATTRIBUTION ANALYSIS

In order to comprehensively describe the observed warming, combined contributions from natural and anthropogenic forcings are required. The role of climate models in assessing the cause of climate change is extremely useful. In D&A studies, it should be analysed whether the

human influences on climate can be distinguished from the natural variability. Climate model simulations are most widely used to estimate the expected fingerprints of climate change in D&A studies. Although climate models are currently the most credible tools available for simulating the responses of the global climate systems to increasing GHG concentration, these are limited by inadequate representation of associated processes and low spatial resolution. It is worth noting that the model simulations cannot extrapolate the same inferences as their configurations are different, and different climate models may lead to different conclusions on attribution. Various D&A approaches have objectively examined the ability of climate models in enabling them for future predictions that would be qualified for historical simulations. Discussion about any model's reliance and uncertainty is essential for a robust D&A analysis. It is worth mentioning here that D&A studies are affected by observed uncertainty, which is beyond the scope of modelling, that can be compensated by considering several independently derived observed uncertainties or by estimating the observational uncertainty effects using random sampling. Quantification of uncertainty due to modelling and forcing is vital, but uncertainty varies across different forcings, such as small for well-mixed GHGs forcing and large for aerosol and land-use change forcings. It can be complicated further because of feedback processes (Forster *et al.* 2007). Aerosols may alter cloud microphysical properties and reduce the amount of solar energy reaching the surface, but at present, our knowledge in this aspect is limited. Any knowledge about volcanic forcing prior to the 20th century is limited unlike the recent history of volcanic activities, which leads to greater uncertainty (Crowley *et al.* 2008). Similarly, prior to the pre-satellite era, solar forcing influences on climate were not evaluated clearly (Gray *et al.* 2010).

### Progress in climate model simulation

As climate model simulations are associated with different uncertainties (as discussed above), it is essential to evaluate them before using further in statistical analysis. This process reduces the chances of spurious detection. The ability of the climate model for simulating the observed changes across a wide range of climate indicators has infused confidence in D&A analysis by reducing levels of uncertainties.

Over the period, across the globe, the evaluation process has greatly expanded with the addition of a range of various performance metrics and performing the process over different hydro-climatic variables (Johnson *et al.* 2011; Flato *et al.* 2013; Sperber *et al.* 2013; Mishra *et al.* 2014; Kumar *et al.* 2015; Sonali & Nagesh Kumar 2016a; Raju *et al.* 2017; Sonali *et al.* 2017a). It is verified that the multi-model ensembles of climate model simulations have been proven to perform better than individual simulations.

With the continual development in climate models from CMIP3 to CMIP5 by improving model simulations with respect to different scenarios, climate change D&A research also has been improved a great deal. Surface temperature simulated by CMIP5 models agrees better with observations compared to CMIP3 (Flato *et al.* 2013). It can simulate most of the important aspects of surface temperature, for example, increasing global scale annual mean surface temperature along with the rapid warming feature during second half of the 20th century compared to the first half, and the immediate cooling following major volcanic episodes. Models are not so good at simulating precipitation compared to surface air temperature. However, large-scale precipitation pattern simulations have been improved substantially since AR4. Cloud simulation still remains a challenging task. Some evidence reported in CMIP5 indicated that the general characteristics of storm track, extra tropical cyclones, ocean heat uptake, tropical Pacific Ocean mean state, important modes of climate variability, namely, intra-seasonal and inter-seasonal phenomena and extreme events were well captured.

Substantial progress was noticed by many model evaluation studies in different parts of the globe (Flato *et al.* 2013). Since AR4 there has been important improvement by the widespread usage of Earth system models (ESMs), which have the capability of using time-evolving emissions of constituents from which concentrations can be computed interactively. ESMs are the current state-of-the-art models, which are improved from the standard models, i.e., atmosphere–ocean general circulation models (AOGCM). Interactive representation of the carbon cycle, aerosol and anthropogenic sulphur dioxide emissions are included in ESMs.

Time-varying ozone (stratospheric) is included in the latest suite of models. Hence, CMIP5 climate models

(climate and Earth system models) are able to simulate many significant aspects of observed climate (Flato *et al.* 2013). Hence, these crucial improvements in CMIP5 promoted our confidence in the model's suitability for application in D&A analysis and for quantitative future projection. CMIP5 includes more comprehensive models with higher-spatial resolution and a wider set of experiments which can address a broader variety of scientific questions.

### CMIP5 experiments

Majorly, CMIP5 includes two types of experiments: long-term (century time scale) and near-term integrations, namely, a decadal prediction experiment which is entirely a new addition. These decadal predictions explore the predictive skill of each variable. Long-term simulation is the core simulation and includes atmospheric model intercomparison project (AMIP) run, a coupled control run and historical run (reflecting both anthropogenic and natural sources). Time-evolving land cover is included for the first time in historical simulations (Taylor *et al.* 2012). Experiments specially designed for climate change D&A studies with only GHG forcing ('historicalGHG'), only natural forcing ('historicalNat') and some single-forcing experiments (such as, aerosol forcing alone, land use forcing alone which fall in the category of 'historicalMisc' experiment) are the new additions to CMIP5 (Taylor *et al.* 2012) which were not available in CMIP3 (Meehl *et al.* 2007b). Information of different experiments majorly employed for D&A analysis is available in Table 1. Some more additions are: 21st century runs with the two other representative concentration pathways (RCPs), namely, RCP2.6 and RCP6, and extension of the future climate simulations up to the year 2300. The CMIP5 projections of climate change described by RCP represent a rough estimate of the radiative forcing by the year 2100. The RCP8.5 (high emissions) and RCP4.5 (mid-range mitigation emissions) scenarios are the other two future projection simulations in CMIP5.

Pre-industrial control simulations are based on non-evolving pre-industrial conditions which serve for the estimation of unforced variability and provide the initial conditions for historical simulations. The model-derived pre-industrial control simulations obtained from the 'piControl' experiment are available over many centuries, incorporating no

**Table 1** | Details of the different experiments available in the CMIP5 archive used for D&A analysis and equivalent CMIP3 terms

Different experiments in CMIP5 archive (Taylor et al. 2012) (employed in D&A analysis)	Description	CMIP3 terms
<i>piControl</i>	Pre-industrial control simulations represent the natural internal variability. They are available over many centuries, incorporating no change in the external climate drivers such as GHG level and solar irradiance, and hence do not exhibit the observed warming	picntrl
<i>historical</i>	Historical simulations are forced by observed atmospheric composition (i.e., both anthropogenic and natural factors) of the 20th century (1850–2005). Time-evolving land cover is included first time for the <i>historical</i> experiment in CMIP5	20c3 m
<i>historicalNat</i>	Historical simulation forced alone by natural external forcings, namely, solar irradiance and volcanic activity	NA
<i>historicalGHG</i>	Historical simulation forced by GHG forcing alone	NA
<i>historicalMisc</i> { <i>historical_AA</i> , <i>historical_LU</i> }	Historical simulation but with other individual or combined forcing agents, such as, <i>historical_AA</i> (forced by anthropogenic aerosols only) and <i>historical_LU</i> (forced by land use change only)	NA

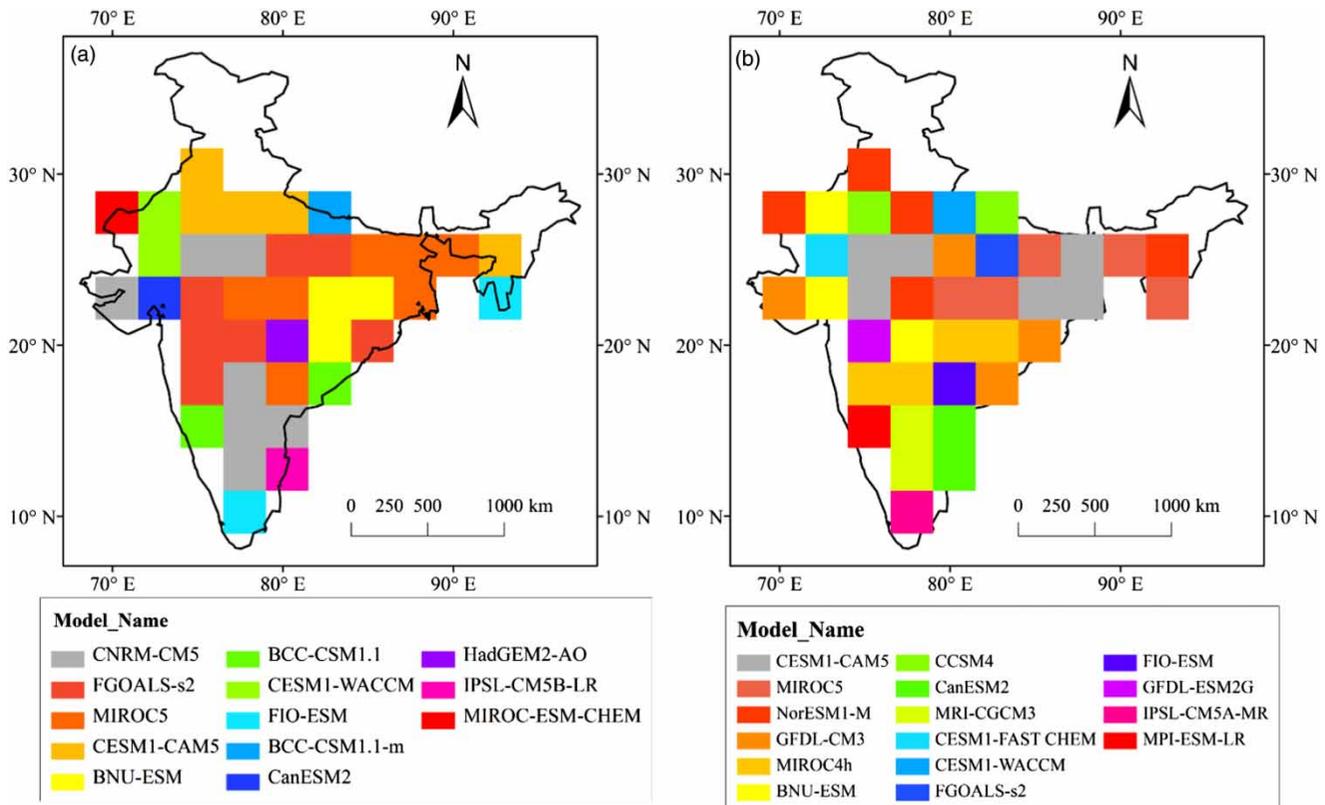
change in external climate drivers such as GHG level and solar irradiance, and hence such control simulations do not exhibit the observed warming. These long pre-industrial control simulations were procured from climate models as these were difficult to obtain from observed data which are not free from the effects of external influences. The equivalent natural internal variability (which is essential for D&A analysis) estimation using too short an instrumental record would not be reliable.

D&A analysis inferences can be improved by considering multi-model simulations instead of a single model. Model discrimination or weighting is less sensitive in D&A analysis compared to future projection, as the consistency of historical and control simulations which are used in D&A analysis can be directly evaluated against observation. A few studies indicated multi-model mean (assigning equal weights) may cancel out some important signals which can mislead future climate projection (Knutti et al. 2010). Weigel et al. (2010) suggested adopting optimum weights in case of large internal variability. However, they have also indicated that multi-model mean assigning equal weight is transparent and a safer option in most cases. Raju et al. (2017) have conducted a detailed assessment to evaluate the strengths and weaknesses of individual climate models over India. Selection of the suitable climate model was based on assigning equal and varying weights to different performance indicators. Inferences of this evaluation study

(i.e., spatial distribution of climate model across India), which is shown in Figure 1, could be directly employed for selecting appropriate models at regional scale. Improvements in AR5 over AR4 include covering global to regional perspectives with a comprehensive focus on spatial pattern across the globe instead of global mean change. The science of attribution depends on climate model simulation, hence, improvement is needed. It should be borne in mind that good quality, unbiased observed and model data sets are crucial to obtain positive attribution results by minimizing the uncertainty associated with attribution analysis.

## DETECTION AND ATTRIBUTION APPROACHES

This section briefly presents the statistical approaches that have been used for climate change D&A analysis (Hegerl et al. 2007b; Hegerl & Zwiers 2011; Bindoff et al. 2013; Ribes et al. 2017). Major components of any D&A studies are observation, a model estimate of the impact of the climate forcings on the climate variables of interest, estimate of internal climate variability (natural unforced variations) and relevant climate forcings (namely, GHGs concentration, solar and volcanic). Four key components and general assumptions of climate change D&A study are presented in Table 2. The robustness of climate change D&A study is majorly dependent on accuracy of model-simulated



**Figure 1** | Spatial distribution of climate models across India based on their performance for varying weights scenario (source: Raju *et al.* 2017).

internal variability. This can also be estimated indirectly from observation. However, there is hardly any difference noticed between internal variability obtained from a model and observation (Bindoff *et al.* 2013). Attribution is not based on statistical assessment alone, and physical judgement is equally essential.

Standard 'frequentist' and 'Bayesian' approaches of statistical inferences are most commonly used for D&A analysis (Hegerl *et al.* 2007b). The standard approach used is to obtain climate responses to a specific forcing. Usually, these responses are represented as the 'fingerprint' of the expected change resulting from various processes acting on the ocean and atmosphere. After that, analysis is carried out to find whether significant manifestation of these fingerprints is present in the observations. Attribution results are usually represented in the form of conventional frequentist confidence interval with a pre-assigned significance level. In this process, expert judgement is essential to check the accuracy of internal variability and estimation of associated confounding factors. In a few particular cases, uncertainty

may be contracted by adopting a Bayesian approach (which adopts prior expectations involved in attribution results), but currently this is not the usual practice.

The simplest technique is to compare the observed changes with the fingerprints obtained from the model simulations with and without anthropogenic forcings. These inferences are used to obtain the likelihood measures in Bayesian decision approach for climate change signal analysis to decide on the most probable competing explanations (Min *et al.* 2004; Schnur & Hasselmann 2005; Stott *et al.* 2010). It considers information from multiple lines of evidence and can utilize independent prior information in the analysis. In the Bayesian approach, there is no formal distinction between 'detection' and 'attribution' as in the conventional frequentist approach. Such analysis fulfils the standard definition criteria of D&A but does not quantify the relative contributions of anthropogenic and natural drivers.

In the conventional frequentist approach, the fingerprints maximize the ratio of the observed climate change

**Table 2** | Key components of climate change D&A studies**Core elements in D&A studies**

1. Observations of single or multiple climate indicators which are relevant for the climate change D&A problem under investigation
2. Estimation of external drivers of climate change (natural/ anthropogenic, namely, solar radiation, volcanoes, aerosols and GHGs) evolved during investigation time period
3. Understanding the impact of external drivers on observed climate indicators under investigation by adopting physically based model
4. Climate internal variability (due to random, quasi-periodic and chaotic fluctuations in the climate system and not externally driven) estimation which is often but not always derived from a physically based model

**General assumptions in D&A studies**

1. Associated key forcings are identified
2. Signal and noise are additive (might not hold for all variables, but to date, non-additive approaches have not been widely adopted (Bindoff *et al.* 2013))
3. Climate models correctly simulate large scale patterns (physically consistent representation of processes and scales relevant to the attribution problem under investigation)

signal to the natural variability noise. Once significant detection is noticed, attribution is carried out in a second step by comparing the observed and model-simulated climate change signals. However, in the Bayesian approach, impact of the evidence (i.e., the observed climate change) is maximized, on the prior probability that the hypothesis of an anthropogenic origin of the observed signal is true. Model uncertainties play a fundamental role in Bayesian framework.

Bertola *et al.* (2019) have applied an attribution framework to analyse the flood changes in 96 different catchments of upper Austria based on Bayesian inference. This has been achieved by comparing various attribution models based on different covariates (drivers of change), and by the priors (hydrological understanding).

**Regression-based fingerprint approach**

One key approach for D&A is the regression-based fingerprint approach (Hasselmann 1979, 1993, 1997; Allen & Stott 2003; Hegerl *et al.* 2007b; Bindoff *et al.* 2013; Knutson 2017). In this approach, observed changes are regressed

onto a model-simulated response pattern to a single or set of forcings; and regression scaling factors are estimated. For a significant detectable change, the scaling factor should be different from zero and to attribute the observed changes to a specific forcing agent, the uncertainty bars associated with scaling factor should encompass unity. A recent development is usage of hypothesis testing with additive decomposition instead of regression. It utilizes the magnitude of responses from the models instead of model patterns for deriving the scaling factor (Knutson 2017; Ribes *et al.* 2017). This approach helps to distinguish the external forced patterns from each other and from the internal variability. The accuracy of inferences, to an extent, depends on the shape of the model-simulated responses to external forcing (North & Stevens 1998).

**Optimal fingerprint approach**

The optimal fingerprint approach is a classical approach which is most frequently used for climate change D&A analysis (Hasselmann 1997; Allen & Tett 1999). This approach has been refined over the years (Huntingford *et al.* 2006; Hannart *et al.* 2014) by formulating suitable multivariate linear regression models, namely, ordinary least square (Hegerl *et al.* 1996) and total least square (Van Huffel & Vandewalle 1991; Allen & Stott 2003; Ribes *et al.* 2013; Ribes & Terray 2013). It is a generalized multivariate regression, where observed change is regarded as a linear combination of externally forced signals. The primary steps involved in optimal fingerprint approach are: (1) dimensionality reduction, (2) estimation of covariance matrix associated with internal variability and (3) linear regression inference with associated uncertainty assessment. Signal-to-noise (S/N) ratio is generally low in the case of variables other than temperature and at regional spatial scale. A thorough description of optimal fingerprint can be found in Hasselmann (1997). In order to improve the S/N ratio, model-simulated responses and observations are normalized by internal variability. There is a need for inverse covariance matrix estimation using the pre-industrial control simulations of climate model or by considering the variations within an initial-condition ensemble. Several difficulties arise in estimating full covariance as it is obtained from control simulations, which are too short for this

purpose. Hence, the dimensionality needs to be reduced. Two approaches are basically followed for dimensional reduction, projection onto the first few spherical harmonics (e.g., [Stott \*et al.\* 2006](#)) and projection onto the first few principal components ([Zwiers & Zhang 2003](#)). After dimensional reduction, it is essential to ensure that the results are robust for the arbitrary choice of truncation, i.e., the sensitivity of the results to the number of spherical harmonics or principal components considered ([Allen & Tett 1999](#); [Ribes & Terray 2013](#)).

At regional scales, risk is severe while optimizing the S/N ratio, as there is a chance of assigning higher weightage to the unrealistic model simulation. Hence, [Allen & Tett \(1999\)](#) proposed a consistency check based on the standard linear regression which can be applied to both space-time and frequency domain approaches for optimal detection. [Allen & Stott \(2003\)](#) described a variant of the optimal fingerprint approach which considers the uncertainty in AOGCM-simulated response to external forcing. The suggested approach is total least squares (TLS) and this is derived from the standard statistic literature. The fundamental difference compared to ordinary least square (OLS) is that it eliminates the systematic bias present in the model simulation with respect to observation.

One more potential alternative suggested by [Ribes & Terray \(2013\)](#) is to employ regularized estimate of covariance matrix, which is a linear combination of the sample covariance matrix and a unit matrix. It provides a more accurate estimate of true covariance by avoiding dimensional reduction ([Ledoit & Wolf 2004](#)). Although regularized estimate of the covariance is found to be more accurate, it does not guarantee the optimal result.

### Temporal optimal detection approach

[Ribes \*et al.\* \(2010\)](#) introduced an original approach referred to as temporal optimal detection approach. It is different from the classical optimal fingerprint approach as it allows to infer the spatial distribution of the detected signal without providing any spatial guess pattern. They applied this approach to data sets of temperatures and precipitation over France. This approach is well suited to regional scale as spatial properties of the internal climate variability

(which is very challenging to estimate at regional scale) are not needed. [Hannart \(2016\)](#) proposed a methodological advancement in the classical optimal fingerprint approach. Several issues may arise with the compartmentalized treatment involved in the classical optimal fingerprint approach. Hence, the proposed approach presents all available data (i.e., observation, model responses and control simulations) in a high-dimensional spatio-temporal format, i.e., represented in a single statistical model.

### Non-optimal fingerprint approach

Qualitatively, non-optimal fingerprint approach can assess the consistency of observed changes with model-simulated changes with respect to different forcings. Thus, non-optimal fingerprint approaches were widely adopted in various studies to analyse the change in different hydro-climatic variables ([Barnett \*et al.\* 2008](#); [Mondal & Mujumdar 2012](#); [Pierce \*et al.\* 2012](#); [Sonali & Nagesh Kumar 2016a](#); [Sonali \*et al.\* 2017b, 2018](#); [Dileepkumar \*et al.\* 2018](#)). A flow chart of the general procedure followed for fingerprint-based D&A analysis is shown in [Figure 2](#).

[Sonali \*et al.\* \(2018\)](#) performed formal D&A analysis by adopting the non-optimal fingerprint approach to assess whether the observed trends in seasonal maximum and minimum temperatures ( $T_{\max}$  and  $T_{\min}$ ) of South India are significantly different from natural variability and whether the anthropogenic signals are evident in them. Signal strengths and corresponding 95% confidence intervals for observations and model simulations under different experiments (historical, historicalNat, historicalGHG, historical\_AA and historical\_LU) were obtained, and shown in [Figure 3](#). Simulations under land use (historical\_LU) and anthropogenic aerosols (historical\_AA) were considered to ascertain the effect of individual forcings. It was found that the observed signal strengths were consistent with multi-model mean (MMM) strengths of historical experiment and close to the MMM signal strength obtained from the historicalGHG experiment. However, it was inconsistent with the signal strengths of historicalNat, historical\_AA and historical\_LU experiments. This analysis established the footprint of anthropogenic impact on southern India's climate. Attribution analysis based on the Budyko hypothesis to ascertain the cause of significant

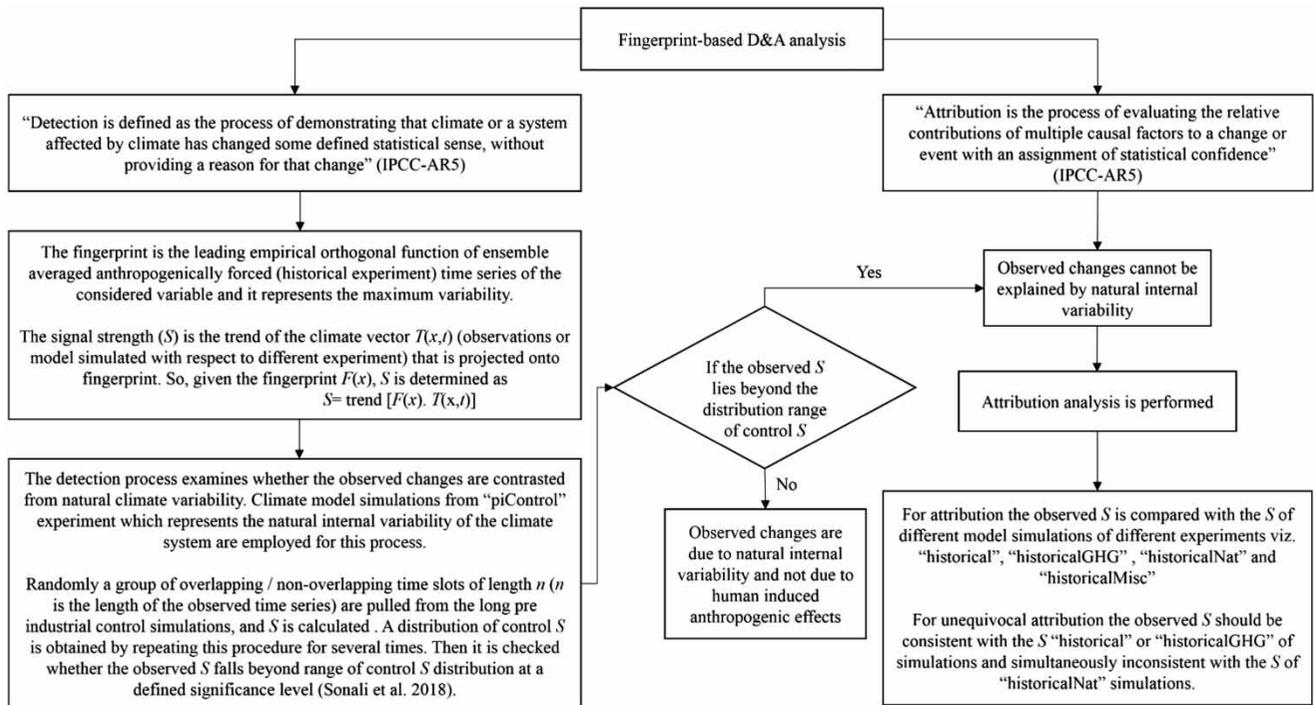


Figure 2 | Flow chart of step-by-step procedure for fingerprint-based D&A analysis.

changes in runoff was widely used (Patterson *et al.* 2013; Xu *et al.* 2014).

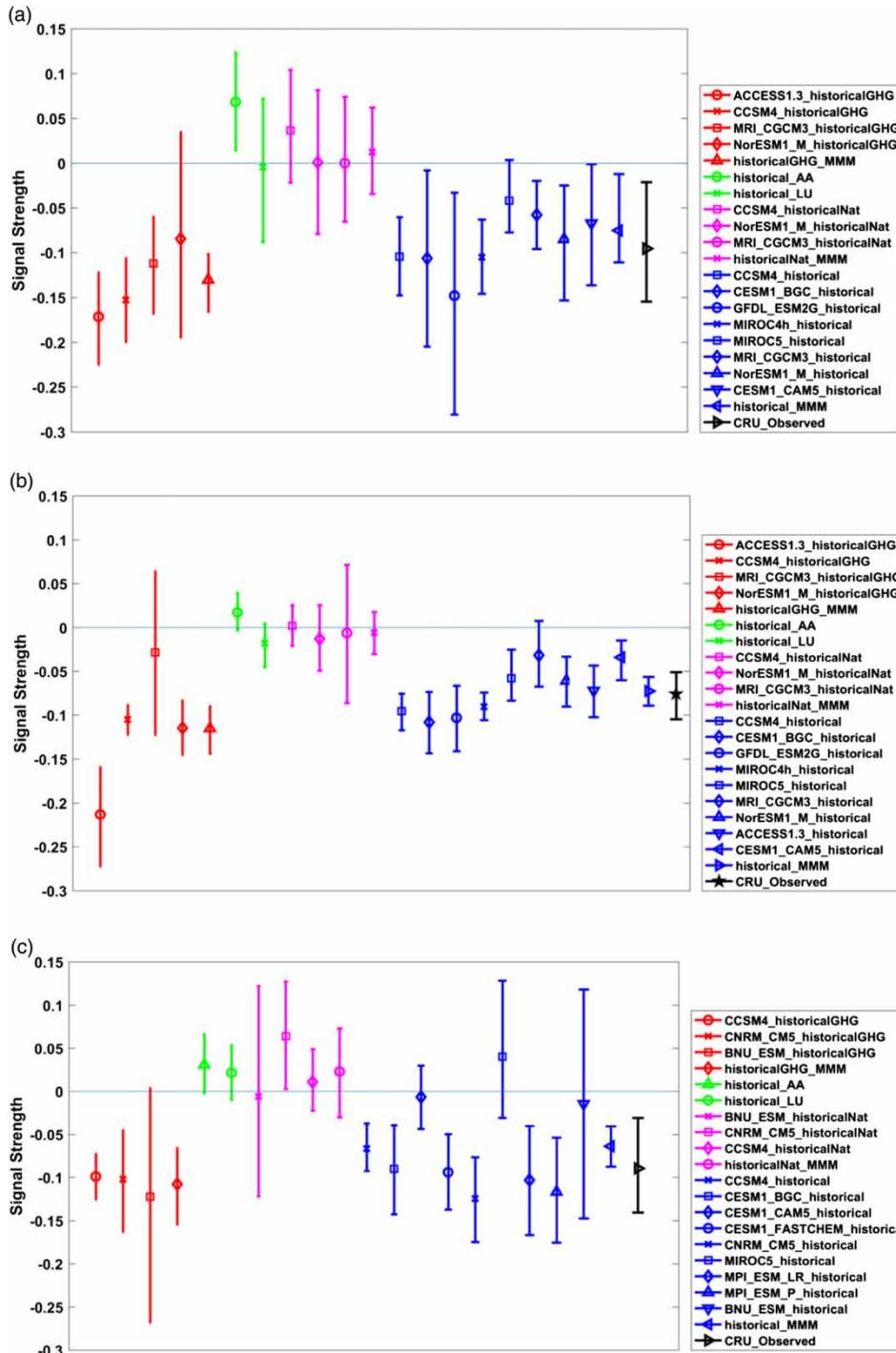
### Other approaches

Various approaches have been employed other than regression-based D&A to analyse recent warming, globally and regionally. Drost & Karoly (2012) showed that the change in global mean surface temperature, land-ocean temperature gradient and meridional temperature gradient cannot be explained by natural internal variability. Smirnov & Mokhov (2009) employed both long-term causality and the widely used Granger causality (which evaluates short-term effects) to analyse the impact of CO<sub>2</sub> content, solar and volcanic activities on rising global surface temperature (GST); and reported anthropogenic factor-CO<sub>2</sub> as the primary cause for rise in GST. Long-term causality mainly focuses on low frequency changes. Granger causality explores the relationships between different variables to infer causal relationships between them and attempts to control influence of a third variable that may be associated with the other two

variables under consideration. Sedláček & Knutti (2012) considered combined warming of the atmosphere and ocean with the latest climate model simulations and indicated anthropogenic forced historical trends are larger compared to the trends due to internal variability. Such physically based arguments can complement the optimal fingerprint attribution approach.

There are few studies available on the application of multi-variable D&A. Multi-variable attribution yields more power compared to the single-variable attribution studies in discriminating between different external forcing and internal variability (Stott & Jones 2009; Pierce *et al.* 2012) and it also furnishes a strict test for climate model. A multi-variable fingerprint consisting of temperature and salinity showed a stronger signal of climate change compared to the signals considering each variable separately (Pierce *et al.* 2012).

Nonfingerprint-based D&A approach is simple (where regression and pattern scaling is not involved), and compares observation and model-simulated time series to analyse whether the observed changes are consistent with the natural internal variability or human-induced



**Figure 3** | Signal strengths and their 95% confidence interval for various model experiments over South India. Individual and multi-model mean (MMM) and observation. Signal strengths are shown consecutively for *historicalGHG*, *historical\_LU*, *historical\_AA*, *historicalNat* and *historical* experiments for individual model and then MMM. Observed signal strengths are marked in black. (a) Pre-monsoon  $T_{min}$ , (b) monsoon  $T_{min}$  and (c) post-monsoon  $T_{max}$ . (Source: Sonali et al. 2018).

anthropogenic impact or the combination of both (Sonali & Nagesh Kumar 2013, 2016b). This approach is suitable for sub-regional scale and is subjected to

uncertainty due to observation, model simulation, climate forcings, model response and simulated internal climate variability.

Deser *et al.* (2016) introduced atmospheric circulation analogues to elucidate the physical mechanisms underlying internal and forced components of winter temperature trends over North America. They also analysed the contribution of atmospheric circulation alone. DelSole *et al.* (2011) suggested an approach to separate the forced and unforced components by maximizing the integral time scale.

The multi-step attribution approach has been widely adopted in a growing number of climate change and extreme event attribution studies. Details about the multi-step attribution are explained in the section 'Weather and climate extreme events attribution'. According to Hulme

(2014), extreme event attribution can be analysed with four approaches, namely, physical reasoning, statistical analysis of time series, estimating fraction of attributable risk (i.e., risk-based approach) and the philosophical argument that there are no purely natural weather events. Among all these approaches, risk-based approach was widely used as it can assess the possible anthropogenic influence on an extreme event. Details about the risk-based approach can be found in the section 'Weather and climate extreme events attribution'. Progress in climate change D&A approaches over the last few decades is shown in Table 3.

**Table 3** | Different approaches employed for climate change D&A studies

Approaches	Study
<b>Optimal fingerprint</b>	
Most popular approach until IPCC AR4 (contribution of external forcings via the estimation of so-called scaling factors, in a linear regression model)	Hasselmann (1979, 1993); Hegerl <i>et al.</i> (1996)
<i>Variants of optimal fingerprint</i>	
1.1. Ordinary least squares	1.1. Hasselmann (1997); Allen & Tett (1999)
1.2. Total least squares	1.2. Van Huffel & Vandewalle (1991); Allen & Stott (2003)
1.3. Errors in variables	1.3. Huntingford <i>et al.</i> (2006); Hannart <i>et al.</i> (2014)
<b>Potential alternatives to optimal fingerprint</b>	
1. Regularized optimal fingerprint (ROF) (regularized estimate of covariance matrix more accurately by avoiding dimensional reduction)	1. Ribes & Terray (2013); Ribes <i>et al.</i> (2013)
2. Temporal optimal detection method	2. Ribes <i>et al.</i> (2010)
3. Integrated optimal fingerprint	3. Hannart (2016)
4. New statistical approach to climate change D&A that is based on additive decomposition and simple hypothesis testing	4. Ribes <i>et al.</i> (2017)
5. Long-term causality and Granger causality	5. Smirnov & Mokhov (2009)
6. Multi-variable attribution	6. Stott & Jones (2009); Pierce <i>et al.</i> (2012)
<b>Non-optimal fingerprint</b>	Barnett <i>et al.</i> (2008); Mondal & Mujumdar (2012); Pierce <i>et al.</i> (2012); Sonali & Nagesh Kumar (2016a); Sonali <i>et al.</i> (2017b, 2018); Dileepkumar <i>et al.</i> (2018)
<b>Bayesian</b>	Min <i>et al.</i> (2004); Schnur & Hasselmann (2005); Hegerl <i>et al.</i> (2007b); Stott <i>et al.</i> (2010)
<b>Approaches for event attribution</b>	
1. Risk-based approaches: 'attributable risk' and 'attributable magnitude'	1. Dole <i>et al.</i> (2011); Field <i>et al.</i> (2012); Hoerling <i>et al.</i> (2013)
2. Extreme event attribution based on AGCM simulation	2. Graff & LaCasce (2012); Dong <i>et al.</i> (2017)
3. Other approaches: physical reasoning, statistical analysis of time series and the philosophical argument	3. Hulme (2014)

## Summary of D&A approaches

An overview of different key approaches adopted for climate change D&A studies and benefits/issues associated with them have been discussed thoroughly in the section 'Detection and attribution approaches'.

'Frequentist' approaches are widespread in the climate science community and frequently employed for climate change D&A studies. They basically draw inferences about the contribution of external forcing to an observed change. Expert judgement is essential to check whether the internal variability and potential confounding factors have been estimated properly. In the frequentist approach, anthropogenic-induced changes are detected via fingerprints (or optimal filter) which maximize the ratio of climate change signal to the natural variability noise. Once the first step detection is achieved, then attribution is performed.

However, in Bayesian approaches, which are based on a posterior distribution that combines evidence from the observations with prior information, detection and attribution are not regarded separately. The optimal filter plays a crucial role as it maximizes the impact of evidence that the observed changes are anthropogenic. It probabilistically describes all information or the sources of uncertainty that enter into a given analysis, and considers the integrating information from multiple lines of evidence as mentioned. Hence, Bayesian approaches are of interest in climate research. However, Bayesian studies published to date have inferred similar conclusions which are consistent with those obtained employing frequentist approaches.

Fingerprint approaches have been adopted extensively and are the most popular to date for climate change D&A studies. Over the period, methodological developments in the fingerprint approach are discussed thoroughly in separate sub-sections under the section 'Detection and attribution approaches'. It is difficult to recommend the best approach for D&A analysis. Advances in science involve new approaches and it depends which approach should be employed based on the requirement.

## DETECTION AND ATTRIBUTION OF LONG-TERM CHANGES IN THE HYDRO-CLIMATIC VARIABLES

Since AR4, stringent quality controls on *in situ* hydrological data sets have been achieved facilitating better climate change D&A analysis. Improved quality assessment and rigorous review processes (validation) were set up to obtain better and lengthened satellite data and derived products, which could potentially offer accurate climate change D&A assessment. Comprehensive D&A review studies were reported by [Stott \*et al.\* \(2010\)](#) and [Trenberth \(2011\)](#) considering changes in different crucial components of the water cycle.

### Hydro-climatic variables

In addition to temperature analysis, scientific attribution of observed hydro-climatic changes, climate-related risks and hazards to human influence can extend to many other aspects such as changing patterns in different variables like precipitation, streamflow, humidity and ocean heat content and will help better to cope with the adverse conditions associated with the rising climate change risk. D&A studies have now moved beyond 'temperature-only' analysis and are more challenging in the case of hydrological variables because of the length and quality of the observed data sets.

The sparse observational coverage of precipitation and continuing uncertainties in the climate model simulations of precipitation have not been resolved to a full extent and remain a challenge to performing accurate precipitation change D&A analysis ([Wan \*et al.\* 2013](#)). It is essential to examine the observational data which are generally constrained by station data sets. A few studies found less variability in precipitation simulation compared to observation in tropics because of the high variance in climate model simulations ([Polson \*et al.\* 2013](#)). D&A of long-term changes in the hydrological variables such as soil moisture, streamflow and evapotranspiration at continental and global scales were analysed thoroughly in recent decades ([Jung \*et al.\* 2010](#); [Seneviratne \*et al.\* 2010](#); [Mondal & Mujumdar 2012](#); [Sheffield \*et al.\* 2012](#); [Alkama \*et al.\* 2013](#); [Douville \*et al.\* 2013](#); [Patterson \*et al.\* 2013](#); [Gudmundsson \*et al.\* 2019](#)).

These variables are largely sensitive to non-climatic human influence such as land use change. Consideration of this influence is of utmost importance while attributing the detected changes. Derived indices such as Standardized Precipitation Index (SPI) and Palmer Drought Severity Index (PDSI) are used to assess the changes in these variables. SPI and PDSI are popular indices and are used to assess the impact of climate change on droughts. These variables are subjected to large modelling uncertainties, and short and sparse observational records limit the quality of D&A analysis. Using the new guidance it is possible to attribute the change in the probability of occurrence of an event which has not yet occurred. To date, D&A studies have been carried out extensively at a regional scale and mostly based on a limited number of climate models.

Better water resources management and adaptation strategies require reliable predictions of the water cycle. [Hegerl et al. \(2018\)](#) extensively discussed the challenges in capturing the expected changes in the global water cycle (including the key variables, humidity, precipitation, precipitation minus evaporation and salinity). Strong evidence indicated that the changes in the water cycle could be explained by hydrological responses to increased GHGs ([Liu & Xia 2011](#)). The IPCC AR5 reported that human activity has likely influenced the global water cycle since 1960, and there is an increase in high-latitude precipitation, global-scale atmospheric humidity and precipitation extremes. [Yuan et al. \(2019\)](#) have attributed the change in vegetation coverage to the change in meteorological factors such as temperature and precipitation and indicated land use change as a major contributor.

To date, one of the most important and visible findings is the attribution of global temperature change to human causes. [Stott \(2003\)](#) carried out a series of optimal detection analyses considering six separate land areas of the Earth, namely, North America, Asia, South and Central America, Africa, Australia and Europe (covering almost all continents except Antarctica). Significant anthropogenic warming trends in all the continental regions were observed, and possible warming due to black carbon which led to reduction in net aerosol cooling in Asia was noticed. The recent global warming hiatus during 1998–2012 was attributed possibly to cooling contribution from internal variability, low confidence in aerosol forcing

trend and contracted external forcings (solar and volcanic) trends ([Knutson 2017](#)).

Evidence of anthropogenic influence on global precipitation changes over land (which is dominant in northern mid-to-high latitudes) since 1950 are presented in AR5. It also reported an increase in atmospheric specific humidity since 1973. There is a significant change in the latitudinal redistribution of precipitation within tropics by shifting the position of the Intertropical Convergence Zone ([Stott et al. 2010](#)). Globally, there is an increase in heavy precipitation over the second half of the 20th century.

Precipitation pattern simulations are broadly similar in both CMIP5 and CMIP3. However, analysis at regional scale D&A based on those simulations is difficult because of poor observations and low S/N ratio. Due to low S/N ratio it is difficult to isolate different external forcing at regional scale. The ability of climate models to detect and attribute the impact of anthropogenic forcing on precipitation is more difficult compared to temperature. [Zhang et al. \(2007\)](#) compared the observed and model simulated land precipitation changes averaged over latitudinal bands during the 20th century. They reported that these changes cannot be explained just by internal climate variability or natural external forcings, as anthropogenic forcing contributed significantly. [Liang et al. \(2019\)](#) analysed the cause and effect relationship between land use change and regional rainfall by hypothesizing that a sudden land use change led to a strong statistically significant change in rainfall over specific regions of Australia.

In AR4 it was mentioned that the observed increase in the atmospheric water vapour over oceans could be due to human-induced anthropogenic effects, as this change is consistent with the changes owing to anthropogenic effects on sea surface temperature (SST), raising drought severity and variability in the latitudinal distribution of global rainfall.

It is difficult to assess streamflow and drought changes as these are associated with many factors such as climate, land use, water use efficiency by plants and catchment properties ([Stott et al. 2010](#)). Attribution of changes in streamflow is essential for optimal water resources management. However, it is difficult to attribute the changes in streamflow to different driving forces such as human influences and natural factors. [Alkama et al. \(2013\)](#) analysed the global streamflow (60% of global discharge data were analysed

using reconstructed data) and indicated no significant change over the period 1958–1992. However, significant changes were found on considering larger reconstructed streamflow record. Reasons for change in global streamflow are still unclear. Global scale streamflow changes were assessed by Gudmundsson *et al.* (2019) considering multiple regions and multiple indices (mean and extreme) using regional trend approach, and the trend magnitudes for individual stations across the globe were reported. They mentioned that the spatial change patterns are complex and, hence, prevented any simple generalization of the regional changes to global scale. Vicente-Serrano *et al.* (2019) have used multiple linear regression and step-wise regression to attribute the detected changes in streamflow to changes in land use, atmospheric evaporative demand and precipitation. Barnett *et al.* (2008) analysed changes in streamflow centre timing, seasonal temperature and melting of snow pack during the second half of the 20th century. They ascertained a detectable change in the hydrological cycle of western USA, and attributed 60% of the changes to human-induced anthropogenic influence. Across the globe, a number of D&A analyses have been conducted to assess the hydrological changes at river basin and sub-basin scales (Liu & Xia 2011; Jia *et al.* 2012; Mondal & Mujumdar 2012; Patterson *et al.* 2013; Sonali *et al.* 2017b). Gudmundsson *et al.* (2017) showed that the observed north–south contrast in Pan-European river flow was captured by climate model only if human-induced impact is included.

Observational constraints exist globally although evapotranspiration change investigations are underway. The global annual evapotranspiration has increased (Jung *et al.* 2010; Douville *et al.* 2013) and few regional studies have indicated the same for the present and future (Johnson & Sharma 2010; Huo *et al.* 2013). D&A-considering evapotranspiration studies have been performed in a limited region and human-induced anthropogenic effect is evidenced in limited regions (i.e., the middle and high latitude of the northern hemisphere) over the globe (Bindoff *et al.* 2013). Jung *et al.* (2010) showed that the global annual evapotranspiration has increased significantly during the period 1982–1997, but after the major El Niño event in 1998, this increase ceased until 2008. This change was majorly due to moisture limitation in the southern hemisphere.

Continental scale evapotranspiration changes are certain (Jung *et al.* 2010), but never attributed to human-induced anthropogenic influence. Douville *et al.* (2013) indicated that these changes in global evapotranspiration could not be explained without invoking the anthropogenic radiative forcing effects. Contribution of rising temperature to evapotranspiration is usually compensated by the effects of wind speed and sunshine hours. The contribution of maximum temperature to change in potential evapotranspiration is significant compared to minimum temperature (Sonali & Nagesh Kumar 2016b). Huo *et al.* (2013) indicated that the decrease in evapotranspiration over arid regions of China during 1955–2008 is due to decline in wind speed.

### Large-scale atmospheric circulation variability

Atmospheric circulation which is large-scale movement of air masses is majorly derived by uneven heating of the Earth's surface, orographic effects and land–sea thermal contrast. It is an important causative factor for regional climate change and climate variability. Since the last decade, studies have been performed to assess the reason behind changes in circulation-related climate phenomena and modes of variability such as widening of tropical circulation and Northern and Southern Annular Modes (NAM and SAM). Various studies indicated a poleward shift of Hadley cells which leads to the widening of the tropical belt, but with different magnitudes. These studies had attributed the expansion of northern and southern Hadley cells to stratospheric ozone depletion and global greenhouse warming. A few studies had also indicated that the changes in other climatic phenomena such as El Niño-Southern Oscillation (ENSO), Indian Ocean Dipole (IOD) and Pacific Decadal Oscillation (PDO) could possibly be attributed to human-induced anthropogenic effects with a low confidence (Bindoff *et al.* 2013). A number of studies presented in IPCC AR5 had applied fingerprint-based D&A approach and indicated human influence on changed SLP pattern since 1951 globally.

### Changes in ocean properties

Oceans are one of the major components of the Earth's energy balance. Significant detection of anthropogenic

influence is possible by analysing each ocean basin separately by considering associated modelling and observational uncertainties, and large internal variability at smaller scales. [Pierce et al. \(2012\)](#) provided more compelling evidence of contributing anthropogenic sources in changing various ocean properties such as ocean heat content, salinity, oxygen and ocean acidification and change in sea level rise at regional scale during the second half of the 20th century.

Ocean heat content has increased since the mid 20th century globally, matching with the net radiative imbalance in the climate system ([Bindoff et al. 2007](#)), whereas the changes are less certain regionally. Considering global climate models from CMIP5, [Pierce et al. \(2012\)](#) has established a D&A study on ocean temperature change. They found that observed changes in upper ocean temperature are inconsistent with natural internal and external (solar fluctuation volcanic eruption) climate variations and consistent with the anthropogenic-induced atmospheric changes.

Ocean salinity is an important climatic variable as it helps to assess the hydrologic cycle. Anthropogenic influence on global ocean salinity changes has been discernible since 1960. Change in global sea level rise has occurred majorly due to thermal expansion and glacier melting, which cannot be explained by natural internal variability alone ([Hegerl et al. 2007b](#)). Global sea level rise budget during the 20th century has helped to assess the relative contribution of different drivers ([Gregory et al. 2013](#)).

Studies focusing on sea level change D&A to anthropogenic influence are currently limited on ocean basin scales, due to a lack of sophisticated approaches which have the ability to separate the natural variability from the anthropogenic contribution.

Studies focusing on the oxygen change in the ocean are limited, although oxygen is an important physical and biological tracer in oceans. A recent global-scale study by [Helm et al. \(2011\)](#) indicated a significant change in oxygen in the ocean and reported that it has decreased significantly in the mid latitudes of both the hemispheres. Due to a paucity of oxygen observation in the ocean, detectable anthropogenic influences are difficult to recognize, but the physical factors which affect oxygen change in ocean such as change in ocean heat content, ocean stratification and

change in surface temperature have indicated human-induced anthropogenic effects to some extent ([Bindoff et al. 2013](#)). However, the change in ocean acidification is strongly attributed to anthropogenic CO<sub>2</sub>.

### Changes in cryosphere

Changes in the cryosphere (frozen water part of the Earth) system, which includes loss in sea ice, ice sheet, ice shelved, glacier and snow cover, is an important part of the Earth's energy budget. Major changes in Arctic and Antarctica are a matter of critical importance globally.

Rapid changes in sea ice of the Arctic due to rapid increase in Arctic temperature have been indicated in several studies. The major factors which cause these changes are global long-term warming, internal climate variability at different time scales and Arctic amplification feedbacks ([Notz & Marotzke 2012](#)).

Sea ice extent in the Antarctic has increased and there is an overall increment in the sea ice extent in the southern hemisphere. This upward trend in the sea ice extent is not consistent with natural climate variations ([Turner et al. 2013](#)), which may be due to limited observed record. Previous studies suggested that the ozone depletion may have caused the increase in sea ice extent in the Antarctica ([Bindoff et al. 2013](#); [Turner et al. 2013](#)). However, recent studies have clarified the issue by showing decreased trends in sea ice extent with respect to stratospheric ozone depletion ([Bitz & Polvani 2012](#)). It was also indicated that the sub-surface warming and increased freshwater input might have resulted in lack of sea ice melting in Antarctica ([Bindoff et al. 2013](#)).

Changes in ice sheet and glacier are local and precluded any D&A study as it is not simulated distinctively in climate models. The ice sheets in Greenland and Antarctica are a source of fresh water to the ocean, important contributors to global sea level rise and crucial for changing climate as these amplify the polar surface temperature ([Pritchard et al. 2012](#)). Whereas regional model simulation indicated nonlinear increase in Greenland surface melting with rising temperature ([Fettweis et al. 2012](#)), various regional modelling and observational studies have established anthropogenic forcing as the major cause for Greenland ice sheet melting since 1993 ([Bindoff et al. 2013](#)). Due to

the shortage of available observational records, the variability in ice sheet loss in Antarctica was poorly assessed and clear scientific evidence about the contributing factors of Antarctic mass loss are not compiled so far. A substantial glacier mass loss since 1960 is mostly due to human influence.

Both satellite and *in situ* observations have confirmed the reduction in northern hemisphere snow cover extent over the last 90 years and it was maximum during the 1980s. Various formal D&A studies have suggested anthropogenic contribution for this reduction (Pierce *et al.* 2008; Rupp *et al.* 2013).

### ATTRIBUTION OF LONG-TERM CHANGES IN CLIMATE EXTREMES

Over the time, additional evidence on discernible human influence on global climatic change has been reported in different assessment reports. Both IPCC AR4 and IPCC Special Report on Managing the Risks of Extreme Events and Disasters Advance Climate Change Adaptation (SREX) reports have accumulated strong evidence of anthropogenic influence on climate extremes based on past and projected changes after reviewing multiple assessments across the globe, and this outcome is usable in disaster risk reduction and climate change adaptation. The cause of observed warming was assessed and briefly described in Chapter 10 of IPCC AR5 (Detection and Attribution of Climate Change: From Global to Regional).

The role of human influence on climate extreme characteristics such as frequency and intensity is important to discuss. There is a rapid increase in the frequency of unusual seasonal and annual mean temperatures over many regions worldwide, and is attributed mostly to human-induced anthropogenic effect (Stott *et al.* 2011). These findings are robust to different data sets and approaches used for processing. Urban population has already been accounted to be more than 54% of the total global population. Hence, devastating damage due to urban flooding has increased significantly over time.

The recent IPCC report (Bindoff *et al.* 2013; Xu *et al.* 2015) has indicated that the frequency and intensity of extreme precipitation events have escalated due to the

impact of climate change. Morak *et al.* (2013) analysed the changes in the frequency of hot and cold temperature extremes over a range of spatial scales, and by employing both optimized and non-optimized fingerprints had confirmed the human-induced anthropogenic contribution in the detected changes. Zwiers *et al.* (2011) reported that the significant changes in various temperature extreme indices over land can be explained by the combined influence of natural and anthropogenic forcings at global and various regional scales. A number of studies have analysed daily data-based temperature and precipitation extreme indices at global, continental and regional scales (Alexander *et al.* 2006; Meehl *et al.* 2007a; Alexander & Arblaster 2009; Rahmstorf & Coumou 2011; Stott *et al.* 2011; Zhou & Ren 2011; Fischer & Knutti 2014; Easterling *et al.* 2016; Vinnarasi *et al.* 2017; Mukherjee *et al.* 2018; Dimri 2019). It is mentioned that the effects of urbanization, land use change and urban heat resulted in significant global mean surface temperature trend. Easterling *et al.* (2016) provided a detail discussion on D&A of climate extremes and suggested to minimize the uncertainty in attribution result by adopting satellite-based data sets for attribution analysis which is now available for longer time periods.

Some additional evidence, such as stronger contribution of anthropogenic forcing in changing characteristics of extreme temperature indices (namely, intensity and frequency) since the mid 20th century on a global scale are included in the latest analysis compared to the SREX assessment. The heavy precipitation has increased globally as temperature increases. Cause-and-effect relationship between changes in external (natural/anthropogenic) forcing and extreme precipitation had not been established until IPCC AR4.

The recent studies suggested that the change could be explained by external anthropogenic forcing resulting due to the heightening in atmospheric moisture content, and it is not associated with natural causes. Min *et al.* (2009) found a detectable influence of anthropogenic forcing in precipitation extremes by analysing an ensemble of GCM simulations over the second half of the 20th century at global, hemispherical and continental scales. Changes in different components of the hydrological cycle which have been detected with anthropogenic influences are directly connected to extreme precipitation changes (Stott *et al.*

2010). However, due to limited direct evidence, observational coverage and uncertainty in the extreme precipitation simulation, AR5 inferred that ‘the anthropogenic forcing has contributed to global intensification of extreme precipitation events with a *medium confidence* during the latter half of the 20th century where adequate observations were available for assessment’ and this inference is in agreement with SREX (Field *et al.* 2012).

Detection of anthropogenic influence at regional scale is limited and studies have indicated an expected increase in extreme precipitation with warming. Both observation and future projected model simulations from CMIP3 and CMIP5 have supported the association of extreme precipitation with warming. However, global mean precipitation is not affected because of energy restraints (Balan Sarojini *et al.* 2012), and the mean precipitation is expected to increase at a slower rate compared to extreme (Allen & Ingram 2002).

Drought is a complex natural hazard and least assessed as it is difficult to monitor. It is caused by geographical and various climatic factors such as precipitation, temperature, wind and solar radiation. Other than climatic variables, soil moisture and land surface conditions play crucial roles in analysing drought. Based on global Palmer Drought Sensitivity Index (PDSI) assessment, AR4 established that no significant evidence is available on the influence of anthropogenic forcing in increasing drought risk during the latter half of the 20th century (Burke *et al.* 2006). Few studies have indicated the association of droughts in various regions to SST and circulation changes with respect to anthropogenic influence. Based on the observations, SREX (Field *et al.* 2012; Seneviratne 2012) concluded that the confidence in attributing the changing drought patterns during the second half of the 20th century to anthropogenic influence has reduced at regional level. Significant changes in the two important drought-related components, namely, precipitation and temperature changes, are consistent with the expected responses to anthropogenic forcing during the latter half of the 20th century. However, global changes in drought and soil moisture indices over the same period are conflicting. This contradiction could be possibly due to the different forcing fields considered to drive the model, associated uncertainty in that model (Seneviratne *et al.* 2010) and to different time periods considered for assessment. Various

studies have pointed out that the historical trends in multi-variable phenomenon drought is overestimated and it is due to a lack of sophisticated approach, spurious trends in atmospheric forcing and choice of calibration periods (Dail 2011; Sheffield *et al.* 2012). Hence, there is not enough evidence available to support AR4 conclusions regarding global increasing drought trend since 1970. Due to the existing difficulties, AR5 has concluded that the climate change has an impact on long-term change in drought with a low confidence. Evidence of anthropogenic GHG emission contributing to the frequent occurrence of flood and drought are reported in various studies conducted in different parts of the world (Burke *et al.* 2006; Pall *et al.* 2011; Field *et al.* 2012; Hirabayashi *et al.* 2013; Mishra *et al.* 2018).

Anthropogenic influence on extratropical cyclones has not been detected since AR4. However, there is a poleward shift of storm tracks and it is attributed to different causal factors such as oceanic heating (Butler *et al.* 2010), mid latitude higher SST gradient (Graff & LaCase 2012) and change in the large-scale circulation. It is difficult to ascertain the change in storm track intensity thoroughly because of the complexity involved and hence, the global average cyclone activities could not be linked to GHG forcings directly.

Increase in the intensities of the strongest tropical cyclones has been evidenced globally (Elsner *et al.* 2008). However, it is difficult to assess the relative contribution of various anthropogenic or natural factors (Knutson *et al.* 2010). There is a lack of studies attributing the tropical cyclone changes to GHG forcing. Diverse views on tropical cyclone suggest the main drivers to be natural and anthropogenic aerosols and internal variability (Villarini & Vecchi 2012, 2013). A literature review summary of climate extremes is presented in Table S2 in the Supplementary Information.

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## WEATHER AND CLIMATE EXTREME EVENTS' ATTRIBUTION

Extreme events are discrete episodes of extreme weather of unusual climate conditions which have adverse effects on society, and can be explained either by meteorological characteristics or by the consequent impacts. These events can extend to a wide range of spatial (from a few kilometres

to the size of continents) and temporal (from minutes to seasons) scales. Usually, the immediate aftermath of extreme events grabs a great deal of social attention in reasoning out the underlying causes.

There is a general tendency to attribute the extremes confidently or denying anthropogenic influence without scientific consensus which is incorrect. For the last few decades, major responses of climate change are manifested in terms of extreme weather and it is of utmost importance to evaluate the contribution of human-induced GHGs and other external influences on these extreme weather events. Extreme event attribution is relatively a new research field which started with Allen (2003) after an episode of extreme precipitation struck southern UK. Thereafter, extreme event attribution has been attracting major attention globally and is an emerging research area in climate sciences (Wehner *et al.* 2016; Mishra *et al.* 2018; Van Oldenborgh 2018). The special annual issue of the *Bulletin of the American Meteorological Society* discusses worldwide extreme events from the previous year (for example, the fifth edition explains extreme events of the year 2015 by Herring *et al.* (2016)). Extreme event attribution studies seek to determine whether and how the probability of an event is associated with climate change and how global warming would have added to the severity of an extreme event. Event attribution proceeds from science to service, and poses a challenge for both in terms of communication of results. So far only a few studies have focused on specific events (Bindoff *et al.* 2013). There is advancement in the science of event attribution, but the geographical coverage remains patchy. An extensive review on the principles of event attribution can be found in Stott *et al.* (2013) and Herring *et al.* (2016).

Basically, two approaches, namely, 'attributable risk' and 'attributable magnitude' have emerged to pose questions on the possibility of various external drivers causing the extreme weather events. In the 'attributable risk' approach, the event as a whole is considered to address how the external driver may have increased or decreased the probability of occurrence of an event of comparable magnitude, whereas, the 'attributable magnitude' approach addresses how the external driver may have increased the magnitude of an event of comparable occurrence probability. Hoerling *et al.* (2013) analysed the changes in magnitude and

likelihood of the 2011 Texas heatwave employing both these approaches.

In the absence of human influence, it is difficult to evaluate absolute risk or probability of an extreme weather event as these events occur only in extreme conditions due to a self-reinforcing process which complements the initial anomaly. Hence, it is difficult to extrapolate the probability of occurrence of such events from the distribution of less extreme events derived from historical records or from the pre-industrial climate record which is ineffective in simulating high frequency weather. Due to the existing biases in climate model simulation of extreme events, it is not wise to consider absolute probabilities estimation. Hence, a combination of hard-to-test distributional assumption and extreme value theory could be an appropriate choice.

With minor deviations, many studies have analysed how different factors have caused the observed extreme events, instead of claiming a low/high absolute probability of occurrence in the absence/presence of human-induced effects on climate (Hansen *et al.* 2012). However, by ignoring absolute probabilities, uncertainty in quantifying changes in probabilities may arise due to the considered time frame, spatial scale, indicators and the way of framing the event attribution question which could significantly change the apparent conclusion.

Most of the studies have focused on attributable risk approach where the risk is a function of both hazard and vulnerability (Field *et al.* 2012). In the assessment of change in risk, mostly the assumption of 'all other things being equal' criterion (i.e., equal weightage to all the associated drivers, namely, natural drivers and vulnerability) is considered. Hence, with this assumption, change in hazard is directly proportional to change in risk, and presented as fraction attributable risk (FAR) in many studies. FAR ( $FAR = 1 - P_0/P_1$ ) depends on the ratio of  $P_0$  and  $P_1$  (i.e., the probability of an event occurring when the human influence is excluded and included, respectively) rather than absolute values.

However, when the return period of the individual event is greater than the time scale over which human-induced anthropogenic signal generally appears (around 30–50 years), then a multi-step attribution process is followed to obtain the change in frequency. Sometimes, other proxy variables like surface temperature and physically based weather models are used to assess the significance of

extreme weather risk. Otherwise, a statistical model is used to extrapolate the implications of human-induced anthropogenic influence from a known scenario consisting of frequent extreme events. Uncertainties and assumptions are associated in both the processes. [Pall \*et al.\* \(2011\)](#) followed a multi-step attribution process to analyse the floods in the UK in 2000. [Rahmstorf & Coumou \(2011\)](#) suggested an empirical approach to evaluate the attributable risk for the Russian heatwave event in 2010. They fitted a nonlinear trend to temperature and found that increasing trend since 1960 has expanded the risk of heatwave during 2010 to a factor of 5. Although dedicated analysis has not been conducted to assess the contribution of various external drivers causing this trend since 1960, various studies have attributed the change over this period to human influence. [Dole \*et al.\* \(2011\)](#) considered the attributable magnitude approach to analyse the 2010 Russian heatwave and pointed out natural variability as the major driving force. [Trenberth & Fasullo \(2012\)](#) focused on the Russian heatwave and suggested a global perspective is essential to unravel the different drivers associated with individual extreme events. However, [Otto \*et al.\* \(2012\)](#) argued for reconsideration of [Rahmstorf & Coumou's \(2011\)](#) inferences along with [Dole \*et al.\* \(2011\)](#) by framing the event attribution question considering both attributable risk and attributable magnitude approaches. As mentioned earlier, similar conclusions were obtained for the 2011 Texas heatwave ([Hoerling \*et al.\* 2013](#)), but later it was pointed out that the outcomes, i.e., attributable risk and changes in the magnitude, were affected by modelling error.

Extreme poor air quality events, such as in Beijing, the 'Airpocalypse' in January 2013, which mostly resulted from the combination of the emission of pollutants and meteorological conditions, had a serious adverse impact on health and economic vitality. [Callahan \*et al.\* \(2019\)](#) have adopted event attribution metrics suggested by [Differbaugh \*et al.\* \(2017\)](#) to analyse this event to assess the role of anthropogenic climate change.

The frequency of extreme heat waves would double over most parts of the world under 2 °C warming compared to 1.5 °C warming ([Dosio \*et al.\* 2018](#)). Hence, it is strongly suggested to limit the global warming rate to 1.5 °C which could drastically reduce population exposure to extreme heatwaves. [Differbaugh \*et al.\* \(2017\)](#) employed four event

attribution metrics to a suite of four climatic variables which test both punctuated and prolonged extremes, namely, the hottest month, hottest day, driest year and wettest 5-d period.

Mostly the contribution of anthropogenic influence is little with respect to overall magnitude because of the dominant effect of natural random weather variability on a short time scale ([Dole \*et al.\* 2011](#); [Hoerling \*et al.\* 2013](#)). The major advancement since AR4 is the quantification of contributing factors in a particular extreme event (might have happened even during the pre-industrial era) using probabilistic approach.

One more widely adopted approach for extreme event attribution is based on the simulations provided by atmospheric general circulation model (AGCM) for the period of interest forced by defined SSTs with/without considering the anthropogenic influences ([Dong \*et al.\* 2017](#)), and the major limitation could be the lack of explicit atmosphere-ocean coupling as mentioned earlier. [Dong \*et al.\* \(2017\)](#) examined the robustness of such attribution conclusions and concluded that for surface air temperature, change simulation derived from AGCM can be reliable. However, AGCM-derived mean/extreme precipitation and mean circulation in some regions are highly sensitive to atmosphere-ocean coupling, not robust and could lead to erroneous attribution conclusions. [Chen \*et al.\* \(2019\)](#) have adopted a fully coupled ocean atmospheric general circulation model and attributed the recent changes in temperature extremes over China to Asian anthropogenic aerosol (AA) emissions. Impact of aerosols was higher in southern compared to northern China.

With the rise in the number of studies, it is concluded that most of the large-scale warmings are because of increase in atmospheric GHG concentration and hence, with multi-step attribution procedure it is possible to attribute the increase in the probability of regional extreme events to human influence on climate ([Field \*et al.\* 2012](#); [Bindoff \*et al.\* 2013](#)). A summary of the literature review of extreme event attribution is shown in Table S3 in the Supplementary Information.

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## DETECTION AND ATTRIBUTION: DIFFERENT PERSPECTIVES AND IMPLICATIONS

D&A of climate change at continental and regional scales is more challenging compared to global scale ([Zwiers &](#)

Zhang 2003; Stott *et al.* 2010). Several concerns exist in regional D&A analysis, such as estimation of proper contribution of natural internal variability at a regional scale, utility of excluded important regional forcing in the global climate model simulations and non-guarantee of accurate model simulations at regional scale. Along with large scales, evidence from regional studies reflect a growing interest in ascertaining causes and effects of climate change, which can vary significantly across the globe. Policymakers are more concerned about regional inferences obtained from D&A analysis. Various studies have established the significant contribution of anthropogenic influence in changing climate at global and regional scales (Stott *et al.* 2010). Extreme events pose various challenges to society, such as health hazards and crop damage.

Regional D&A analysis is more difficult than at global scale. The contribution of internal variability is amplified at regional scale. Climate model simulations (such as pre-industrial control simulation and historical natural, GHG and miscellaneous forcings) are less dependable at regional scale compared to global scale and it is difficult to apportion responses to different forcings at regional scale.

The crucial challenges in climate change D&A studies at regional scale are due to dominant natural internal variability, uncertainties in the climate model outputs and uncertainties in observational data sets, uncertainty in the regional forcing such as land use change and impact of aerosols. Various studies have been conducted at continental, sub-continental and regional scales, and manifested the human-induced anthropogenic influence on various hydro-climatological entities along with surface air temperature (Barnett *et al.* 2008; Liu & McVicar 2012; Alkama *et al.* 2013; Bindoff *et al.* 2013; Stott *et al.* 2013; Xu *et al.* 2015). Crucial change in surface air temperature over India has been documented, majorly based on trend detection analysis, but only a few studies focus on formal D&A analysis (Sonali & Nagesh Kumar 2013, 2016a; Dileepkumar *et al.* 2018). For a developing country like India, with a population in excess of 1.2 billion, it is essential to analyse the natural and anthropogenic influences on the recent change in climate for proper planning of adaption and mitigation strategies. India, a huge country with the second largest population in the world, is subjected to large seasonal and regional climate variability. It has been observed both by

Sonali & Nagesh Kumar (2016a) and Dileepkumar *et al.* (2018) that the human-induced anthropogenic forcing is the prevalent contributor to the recent warming over temperature homogenous regions of India. Both observations and general climate model simulations have by now affirmed that there is a significant increase in extreme events globally. Mukherjee *et al.* (2018) have reported increasing trends in extreme precipitation and dew point temperature over India during 1979–2015 and indicated that the rate of change is higher in south India compared to north India, and is going to rise further during the late 21st century. The overall focus on climate change D&A study over China remains inadequate. Zhai *et al.* (2018) reported that the existing studies over China have majorly focused on mean and extreme temperature, different heatwaves and extreme temperature/precipitation events, whereas a handful of studies have focused on different hydro-climatic variables (other than temperature and precipitation), such as extreme precipitation, event attribution related to drought, tropical cyclone and complexity involved in the East Asian monsoon. Identification of response patterns of the hydrological cycle with respect to natural internal and external drivers using a formal D&A approach could be a valuable research area with the availability of better observations and model simulations.

### Climate change D&A in a longer-term perspective

Considering a longer-term perspective of climate change, i.e., before the 20th century, it is seen that the anthropogenic and natural forcings played significant roles in driving climate variability at hemispheric scale. Ascertaining the causes of climate change during the pre-industrial era (before the 20th century) could be helpful in better assessment of the present natural climate variability.

Large-scale change in temperature over the past millennium was analysed in many studies as reported in IPCC, AR4. It is indicated that the inter-decadal temperature variability over the northern hemisphere (NH) during seven centuries prior to 1950 was majorly due to natural external forcings. With the availability of more simulations of the last millennium, it was reported that climate models in response to natural external and GHG forcings could simulate the NH temperature change and are consistent with

reconstruction and its uncertainty ranges (Schmidt *et al.* 2012; Bindoff *et al.* 2013). However, the level of agreement between the model simulation reconstruction decreases in the early millennium which could be due to weaker forcing and uncertainty in reconstruction. Various data assimilation studies have provided consistent explanations about the last millennium climate change (Goosse *et al.* 2010). Evidence from various D&A studies are consistent with the modelling studies that infer that the contribution of external forcing is significant during the 16th and 17th centuries in the cooling of NH temperature (Hegerl *et al.* 2007a). Volcanic forcing has an important role in explaining the early cooling episodes (Hegerl *et al.* 2007b).

In a multi-century perspective, it is difficult to discern the influence of solar forcing alone in explaining the NH temperature, although a few analyses could detect the same (Hegerl *et al.* 2007a). Even though solar forcings were at the high end of estimates during the last millennium, these could not explain the recent warming which is verified by both model simulation and D&A analysis. Response to GHG variation during 1400–1900 is noticed in most NH reconstructions (Schurer *et al.* 2013). Orbital forcing may be important in millennial and multi-millennial time scales (Marcott *et al.* 2013).

Focusing on the past regional temperature change, various reconstructions of the European region temperature variability are available and the role of natural and human forcings on seasonal temperatures were emphasized (Hegerl *et al.* 2011). It is difficult to discern the individual forcing responses at regional scale because of noisy reconstructions. However, various studies focused on different regional climate reconstructions and inferred solar influence (Kobashi *et al.* 2013) and volcanic responses (Hegerl *et al.* 2011; Landrum *et al.* 2013). Recent D&A studies added evidence and strengthened the report of AR4, namely, ‘last millennium climate change and variability could be explained with the combination of natural internal variability and responses due to external forcings’. Data assimilation results confirmed the importance of external forcings along with natural variations.

### Climate change D&A implications for future projections

The Earth’s climate sensitivity to change in radiative forcing is a major source of uncertainty in future climate projection.

Results of D&A analysis could be useful to constrain the predictions of future climate change and key climate system properties such as equilibrium climate sensitivity (ECS), transient climate response (TCR) and transient climate response to cumulative CO<sub>2</sub> emissions (TCRE). ECS defines the long-term equilibrium corresponding to a stable ocean–atmosphere system. TCR matches more closely with the variation in past CO<sub>2</sub> concentration and differs from ECS as the distribution of heat between the atmosphere and oceans might not have reached equilibrium state. Constraints on these climate system properties are formulated based on the recent observed climate change, climate modelling information and complementing analysis of feedbacks. Prediction of future climate is strongly dependent on these climate system properties.

These key climate system properties indicate the climate sensitivity and represent the warming at the Earth’s surface due to doubling of atmospheric CO<sub>2</sub> concentrations with respect to pre-industrial levels. TCR is also known as ‘transient climate sensitivity’. TCR is restrained by transient warming and is notably lower compared to ECS. The IPCC AR5 reported a likely range of warming with doubling of atmospheric CO<sub>2</sub> concentration as 1.5 °C to 4.5 °C and 1 °C to 2.5 °C for ECS and TCR, respectively. A less commonly used concept, the Earth system sensitivity (ESS), includes the effect of slower feedbacks such as changes in ice sheets and changes in albedo as a result of changes in the vegetation cover.

### FUTURE DIRECTIONS

Current D&A analyses are useful for scientific evaluation, but progress is still needed to utilize the inferences fully for making policy decisions. Due to various sources of associated uncertainties, it is not clear whether D&A analysis provides an accurate source of information. D&A remains solely a research field and has yet to contribute more to the climate service field (Stone & Hansen 2016). Uncertainties in both forcing and its response are of major concern in climate change D&A analysis at global and majorly at regional scale. A credible estimate of internal variability is ever challenging in D&A studies. Special attention should be paid to these issues. Specific focus should be

devoted to climate change analysis in a multi-century to millennium perspective both at global and regional scales to integrate the present knowledge in ascertaining the internal and forced natural variabilities of the recent past. Consideration of all relevant forcings and their uncertainties simultaneously, proper statistical approach and homogenous data sets could reduce the risk of misattribution to a great extent. D&A analysis results could be implemented in characterization of basic properties (such as ECS and TCR) of the climate system that could be useful for future climate projection.

Invariably, D&A analysis relies heavily on climate models. The significance of various studies suggests that society requires a serious and careful consideration of model projections for future climate change. Climate model evaluation based on historical simulations is of direct relevance to the D&A analysis since it is based on model-derived patterns (i.e., fingerprints) of climate response to external forcings. Conversely, D&A analysis provides inputs to the model evaluation process by analysing the amplitude of modelled responses to various forcings. Models do not have the right balance in simulating historical changes in normal and extreme climates and, hence, D&A analysis considering extreme events usually suffers from the limitation of climate models.

Climate change D&A employs historical simulation (which is the combined response to different forcings) to obtain the fingerprint, which is further used to estimate the contributions of different causal factors to the observed climate change. Ribes *et al.* (2015) used Monte Carlo simulations to suggest different strategies (combinations of forcings), i.e., by designing the set of experiments which could produce the recent GHG-induced warming efficiently. This could be accomplished by suggesting the combinations of forcings which produce the highest accuracy in estimating  $\beta_{GHG}$  (GHG-induced warming scaling factor), which was used in the regression-based statistical model suggested by Allen & Stott (2003). They suggested the optimal strategy (Combination of all + Aerosol only + Natural only forcings) which can be adopted by many modelling centres in the upcoming CMIP6 D&A exercise. They mentioned the allocation of large ensemble size to the weaker forcing. The new phase CMIP6, which was enacted for the betterment of model simulation in every possible way, could be helpful

in D&A analysis. There is always important scope to investigate the influence of upgraded data sets, sampling and model uncertainties on the existing conclusions. Regional scale attribution remains challenging because signal separation is limited by lower S/N ratio due to the dominant impact of internal variability. Important regional forcings (such as land use change and short-lived forcings) should be considered along with improved spatial resolution of global climate models for successful regional D&A analysis.

Periods with prolonged abnormal hot weather known as heatwaves are increasingly becoming common and have a disastrous impact on human health and the environment. Increase in frequency of heatwave is seen in many parts of the world, but it is more predominant over tropical regions compared to other regions. Increase in heatwave frequency is going to be more rapid in future over tropical regions owing to low interannual variability (Herold *et al.* 2017). Recent heatwaves have had a calamitous effect on the biosphere (planet occupied by living organisms). Further, a projected enhancement in duration, intensity and frequency of heatwaves under anthropogenic influence is ineluctable in future (Schoetter *et al.* 2015). Herold *et al.* (2017) reported that low-income countries have faced more adverse temperature extreme conditions compared to high-income countries during the past two decades, not only due to the absence of fair adaption and mitigation efforts, but due to their location near the equator, and thus more vulnerable to global warming impact. This crucial aspect of the ramification of geography has not been considered in the present international climate policy agreements. For densely populated, rapidly developing and highly vulnerable regions, extreme event attribution studies should be more encouraged. A multi-variable attribution which produces stronger climate change signals should be widely adopted for robust and accurate attribution. Despite substantial progress in the science of extreme weather and climate events, there is no unanimity about the best methodology to be adopted for event attribution.

## CONCLUSIONS

The discernible human influence on global climate is a major cause of concern and profound focus should be

devoted to it. The objective of this paper was to review the advances made in assessing different climatic changes across the globe due to human influence and natural variations. Successful adaptation strategies necessitate primal understanding to be obtained from an extensive review on climate change detection and attribution (D&A) analyses. This review majorly discussed the ongoing research on climate change D&A at global, continental and regional scales considering various hydro-climatic variables, role of climate models in D&A analysis, the associated uncertainties, and robustness of the results and inferences. The inferences of D&A studies reviewed here have confirmed the human-induced anthropogenic influence on climate change. One of the key findings in IPCC AR5 is the 'likelihood of the impact of human influence attested in most of the critical components of the climate system is virtually certain'.

New model simulations from CMIP5 have several advantages over the CMIP3 in terms of participation of more numbers of AOGCMs, the addition of new experiments which are necessary for D&A analysis (such as natural forcing only, greenhouse gas (GHG) forcing only), moderate improvement in spatial resolution and parameterizations, and better representation of aerosols.

Various observational and model studies have provided rich evidence of significant increase in the intensity of hot and cold extremes and the number of heatwaves on global, continental and sub-continental levels. Extreme events can have devastating impacts on human society and, hence, assessing the fundamental processes involved with these events are indispensable for future risk assessment, robust climate prediction and framing of climate change policies and adaptation strategies. Major challenges remain in robust attribution of regional changes in extreme events because of poor modelling historical records. Event attribution statements are generally made without clear detection of an anthropogenic influence and, hence, individual events will typically contain caveats in spite of being a rapid growing research field. Despite uncertainty, event attribution studies have progressed to better understanding of the physical mechanisms involved, increasing resolution of climate models and promising newly developed approaches for exploring the roles of different influences on the occurrence of extreme events.

D&A seeks to analyse whether the climate has changed significantly, and its underlying causes. Inferences of D&A analysis have many potential implications. It refines the understanding about human-induced anthropogenic changes in climate. It importunes slashing the GHG emission level if it is the major factor leading to significant change in climate. It is helpful in interpreting the current risk associated with frequent extreme climate events and for accurate future predictions, where traditional assumption of a stationary climate is no longer valid. In a way, D&A studies evaluate the model performance rigorously by comparing it with observations. It can provide useful suggestions to various climate modelling centres based on the model's efficiency and deficiency in different locations across the globe.

Considering future challenges for the science of D&A, to better analyse the present pace of change and to understand the physical processes driving the regional-scale changes, a refined understanding of the effects of external forcings and internal variability is highly essential.

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## SUPPLEMENTARY MATERIAL

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