**Assessing the observed impact of anthropogenic climate change**

Dr Gerrit Hansen*

Potsdam Institute for Climate Impact Research
P.O. Box 60 12 03
D-14412 Potsdam, Germany
E-mail: hansen@pik-potsdam.de
Phone: +49 176 2004 9592

Dr Dáithí Stone

Lawrence Berkeley National Laboratory

1 Cyclotron Road, Mail Stop 50F-1650

Berkeley, California, 94720, U.S.A.

E-mail: dstone@lbl.gov

phone: +1-510-495-8160 fax: +1-510-486-5812

## Abstract

**Impacts of recent regional changes in climate on natural and human systems are documented across the globe, yet studies explicitly linking these observations to anthropogenic forcing of the climate are scarce. Here we provide a systematic assessment of the role of anthropogenic climate change for the range of impacts of regional climate trends reported in the IPCC's Fifth Assessment Report. We find that almost two-thirds of the impacts related to atmospheric and ocean temperature can be confidently attributed to anthropogenic forcing. In contrast, evidence connecting changes in precipitation and their respective impacts to human influence is still weak. Moreover, anthropogenic climate change has been a major influence for approximately three quarters of the impacts observed on continental scales. Hence the effects of anthropogenic emissions can now be discerned not only globally, but also at more regional and local scales for a variety of natural and human systems.**

## Introduction

While evidence is accumulating that anthropogenic emissions are behind recent observed climate trends and also that recent climate trends have impacted natural, human and managed systems, the full causal chain has only been examined for a few isolated observed impacts[e.g. 1–3] or at a generic aggregate level[4,5]. The Intergovernmental Panel on Climate Change's Fifth Assessment Report (IPCC AR5) investigates the detection and attribution of observed impacts to recent changes in climate (hereinafter 'impact attribution') in the contribution of Working Group II (WGII)[6] and the detection and attribution of observed changes in global and regional climate to anthropogenic forcing ('climate attribution' hereinafter) in the contribution of Working Group I (WGI)[7], but does not provide an assessment of the relevance of one for the other.

Our analysis fills this gap by assessing the role of anthropogenic forcing in the climate trends that are reported to cause the impacts specified in the IPCC WGII AR5[6] individually, based on a novel method[8]. In order to assess the confidence in the role of anthropogenic forcing in observed changes in climate for specific regions, seasons, periods and climate variables, we apply an algorithm which i) evaluates the adequacy of observational and climate model data products and ii) investigates the degree to which anthropogenic emissions are a necessary condition for climate model simulations to reproduce observed climate trends (Figure 1, see also online methods).

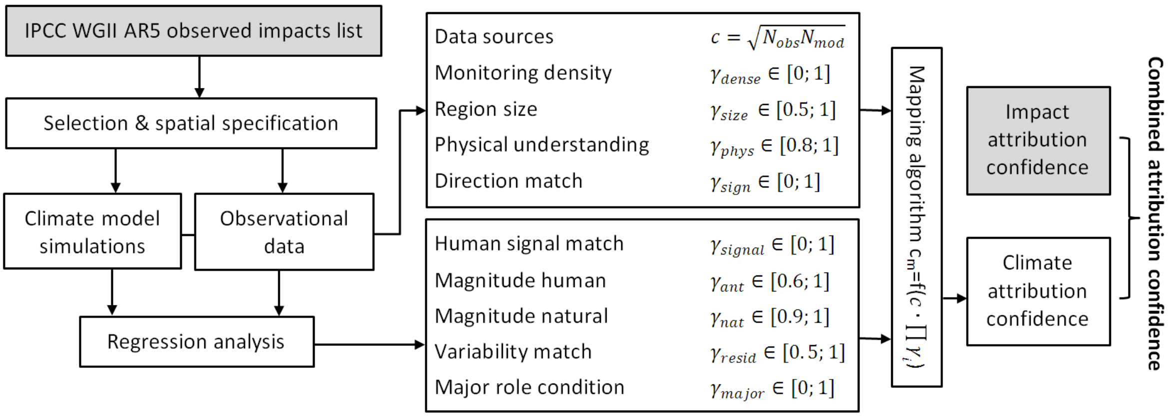


**Figure 1 Schematic showing the approach of this analysis, combining the impact attribution information from IPCC WGII AR5 (grey boxes) with individual climate attribution assessments for the respective region, season and climate variable (white boxes) in order to assess the observed impact of anthropogenic climate change (combined attribution confidence). The analysis follows a new method[8], explicitly accounting for individual steps contributing to confidence in climate attribution (see also online methods). The multiplier ranges for each step $\gamma_i$ are also listed.**

Results are expressed in confidence levels corresponding to the IPCC confidence metric[9], with the addition of a "no confidence" level for cases where the historic climate variations have not been monitored[10], no anthropogenic signal is found in the modelled responses, or the observational data products do not reproduce the direction of change stated in the IPCC AR5. In line with the IPCC WGII AR5 assessment, confidence is expressed for either a *major role* or at least a *minor role* of anthropogenic forcing in the observed climate trend. Finally, the impact attribution and climate attribution assessments are combined by a simple minimum approach to provide a multi-step assessment[10] of confidence in the role of anthropogenic climate change in observed climate-related effects (‘combined attribution’ hereinafter).

Here we provide a systematic assessment for a large range of impacts. Given the varying levels of aggregation of the impacts listed in the AR5, and that our data sources are optimized for global rather than regional application, our approach will not reach the level of accuracy that is possible with a detailed analysis for some individual assessments. Nevertheless, the algorithm considers adequacy and quality of observational data products in addition to examining the agreement amongst multiple observational estimates and climate models, a source of uncertainty that is usually not included in existing studies.

The original list of impacts consists of all regional assessments from Tables 18.5 – 18.9 as well as global statements taken from Table 18.11 in the chapter on ‘Detection and attribution of observed impacts’[6] in IPCC WGII AR5 (hereinafter AR5). Selection restrictions eliminate 19 assessments, for instance whose regional extent is unclear. The analysis is limited to impacts driven by long-term temperature changes over land and in the ocean, including ocean temperature as a proxy for sea ice, and changes in precipitation. Splitting multiple-driver assessments into individual assessments, the resulting list of impacts comprises 118 assessments from all regions and across natural and human systems (see supplementary table S1 for details). Seasonal and spatial characteristics of the relevant climate trends are defined based on the tables, supporting text, and referenced materials in the AR5[6].

In most cases, the AR5 states the direction of the climate trend causing the response in the respective impact system (e.g. 'warming', 'decline in sea ice'). Climate responses to anthropogenic forcing do not necessarily result in monotonic trends in the observed record[e.g., 11], however in order to correspond to the impact statement, the observational and model data need to reproduce the direction of the stated trend. Our analysis explicitly considers the potential role of modes of long-term autonomous variability of the climate system, such as the Pacific Decadal Oscillation, in statistical analysis of the trends, through the consideration of multiple climate model simulations. Impacts are intended to be generically relevant to the past few decades; here we use the 1971-2010 period for all assessments. A minimum of two decades is likely required for detectable trends in global mean temperature due to anthropogenic forcing[12], while three to eight decades may be required at more local spatial scales, depending on location[13]. Similarly, the detection of anthropogenic influence on regional precipitation trends is challenging[14]. For the large majority of examined cases, climate attribution results were insensitive to changes in the period.

**Determinants of confidence in climate attribution**

The algorithm for estimating the confidence in climate attribution starts with a value depending on the number of available data sources, followed by nine evaluation steps, three of which can ~~enforce~~ impose a *no confidence* result (see Figure 1). All but one of the 17 *no confidence* assessments result exclusively from the requirement that observed trends in most of the global observational datasets match the direction of change stated in the IPCC assessment ("sign" step). One reason for this discrepancy might be a mismatch of global observational datasets used here with other, more locally specialised sources of climate trend information underlying the initial statement. Another reason might be strong sensitivity to the period examined for certain cases, such as regions with strong natural climate variability. Figure 2 shows the average penalties arising from each step. The "sign" step stands out as the single most dominant reason for the reduction in attribution confidence for impacts related to precipitation, and for very small regions.

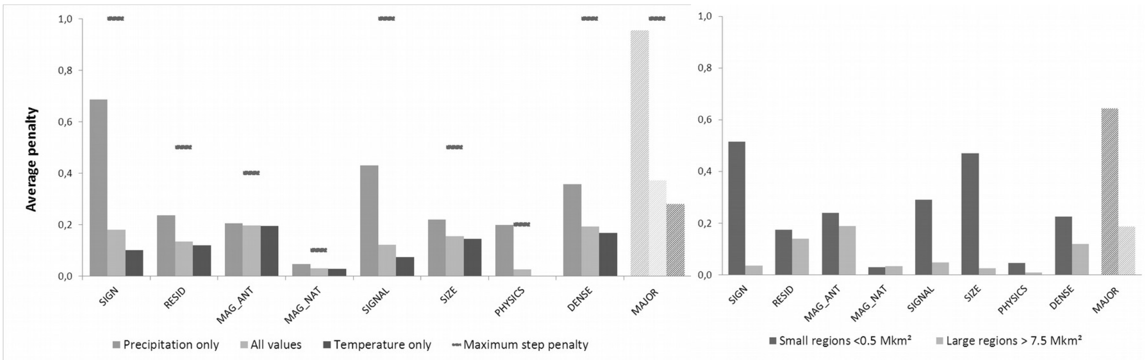


**Figure 2. Average penalties arising from the nine individual steps of the confidence algorithm for the list of impacts analysed. The left panel shows the average contribution to the reduction of the confidence metric for precipitation, averaged across all assessments, and for temperature, with short horizontal lines indicating the potential maximum penalty for the respective step. The right panel compares very small and very large regions. Note that the "major" step does not translate directly into confidence, but also determines the role attribute.**

Insufficient observational monitoring density poses a main limit on confidence (see Figure 2), an effect that is most pronounced for impacts related to precipitation. Note that because of the smaller decorrelation scale the network density must be considerably higher for precipitation than for temperature[8]. Confidence in attributing precipitation trends is generally *low*, with the majority of the respective assessments not yielding a consistent signal across the observational datasets, and 14 out of 16 assessments resulting in lower than *medium* confidence. Region size also emerges as a decisive factor influencing climate attribution confidence, with very small regions showing much lower than average confidence ratings. **While region size is an imposed constraint on confidence in climate attribution in the attribution algorithm, that relationship also holds in the absence of the region size penalty.** In contrast, *very high confidence* in climate attribution is restricted to regions that cover at least 2 million km² and exclusively related to impacts of temperature.

The possibility of comparing the results for the 118 assessments here against results from other studies and assessments[7,15] is limited because of differences in period, season and regional extent covered, and because of our focus on long-term regionally-averaged trends, rather than more complicated signals. Stone and Hansen[8] compare results for a variety of continental and African regions considered in the IPCC AR5 and find that assessments are broadly consistent. Below we discuss two specific cases which point to limitations and advantages of our approach. First, the observed decline in Austral winter (wet season) precipitation in the Australian southwest has recently been linked to anthropogenic greenhouse gas emissions and stratospheric ozone depletion[16]. Our analysis finds high confidence in a minor role of anthropogenic forcing in observed annual precipitation decline for the same region. In line with the exceptional conditions applying in that part of Australia[17], this assessment constitutes the highest confidence finding related to precipitation in our analysis. In contrast, our analysis estimates *no confidence* in the attribution of the recent changes in rainfall in the Sahel to anthropogenic forcing of the climate system, whereas evidence of a role of anthropogenic aerosol precursor emissions and ocean warming related to greenhouse gas emissions has been reported for both the extreme drying period up to the 1980s and the recent recovery of the rains in more bespoke analysis[18,19]. Our *no confidence* assessment results primarily from the lack of a consistent trend over the period 1971-2010 in the datasets, which can be partly explained by the pattern of change: a drying trend from the 1950s through the 1980s, with a partial recovery since the 1990s. While our *no confidence* result could therefore be considered an artefact due to the 'trend' condition inherited from WGII, repeating the analysis omitting the "sign" step, and also for a more recent and an earlier longer period equally resulted in no more than *low confidence*, indicating that climate attribution confidence is limited by additional factors.

**Comparing impact and climate attribution**

On average, the climate attribution assessment results are more confident than the corresponding impact attribution assessments (Figure 3). The climate attribution assessment spans the full range of confidence, whereas the impact attribution assessment is centred at medium values. On the climate side, a systematic analysis is performed without an a priori expectation of the actual anthropogenic signal. In contrast, the initial impact database, by design, looks at areas where impacts would be expected, excludes negatives and reports few statements of *very low confidence*, so the distinction in average confidence is actually understated by these results. Impact attribution confidence is fairly evenly spread for the various climate drivers, while climate attribution confidence is differentiated for the climate variables with lower confidence for precipitation.

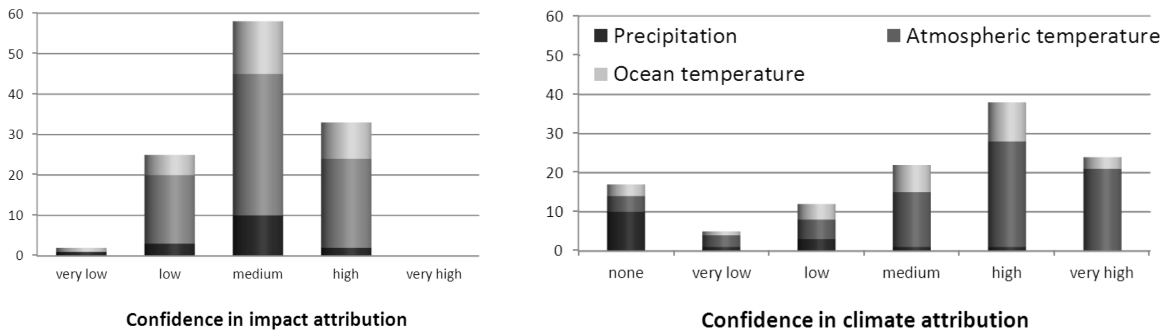


**Figure 3: Comparison of impact (left panel) and climate (right panel) attribution confidence for precipitation, atmospheric near-surface and ocean surface temperature. Vertical axis indicates the number of assessments in the respective confidence bin and shades of grey indicate the corresponding climate variable, i.e. precipitation (16 values), and atmospheric (74 values) and ocean (28 values) surface temperatures.**

However, as can be seen in **Figure 4, no** strong **direct relationship exists between the level of confidence in climate attribution and impact attribution**, though some evidence of a link can be found in statistical analysis (see SI.4 for more detail). Climate assessments that could not be attributed to anthropogenic forcing at all include the full range of confidence levels on the impact side. Similarly, many climate assessments that show *high* or *very high confidence* in a signal of anthropogenic forcing in turn lack substantial confidence in the attribution of corresponding observed impacts. Thus evidence for one of the steps in the attribution chain is ~~a~~ **necessary, but** not ~~in~~**sufficient** ~~condition for evidence of the~~ for combined attribution. While no direct relationship exists between the minor/major role assignments either (see SI.4), for almost half of the assessments examined (57 values), a ‘major role’ is assigned for both impact and climate attribution and consequently in the combined attribution assessment; for 53 of these assessments, confidence is *medium* or higher for both steps.

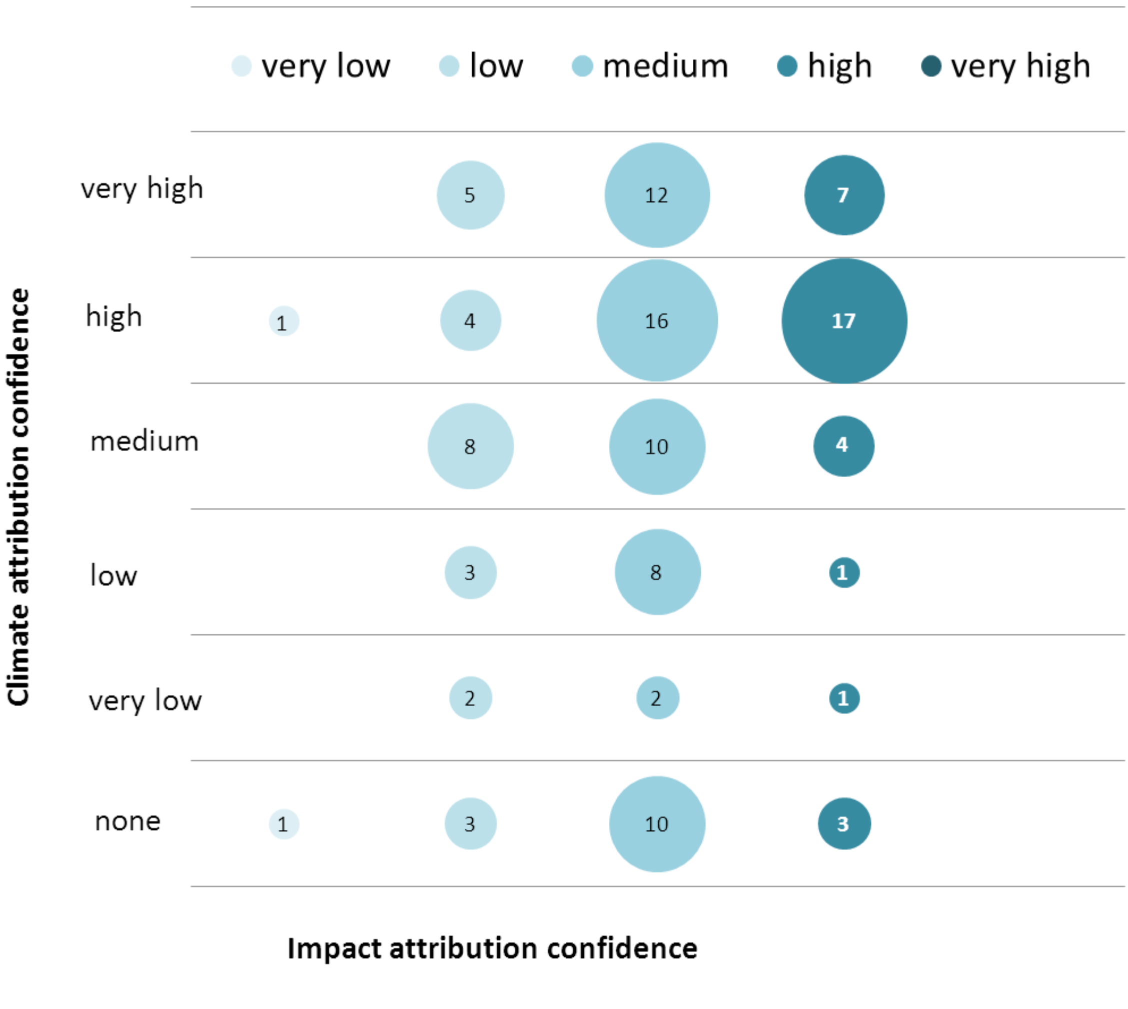


**Figure 4: Distribution of confidence levels for impact attribution (horizontal axis) and climate attribution (vertical axis) for the 118 impact-climate trend pairs analysed. Size of circles indicate the number of assessments in the respective bin.**

**Combined attribution: emissions to impacts**

Confidence in combined attribution and the combined role attribute are estimated by a simple minimum approach: the respective lower value is assigned for both (e.g. *low* and *medium confidence* result in *low confidence*, minor and major role result in minor role). Results are illustrated in Figure 5 through the summary map format adopted by IPCC WGII AR5[20]. Impacts where the associated climate attribution step yields at least *medium confidence* are highlighted in colour.

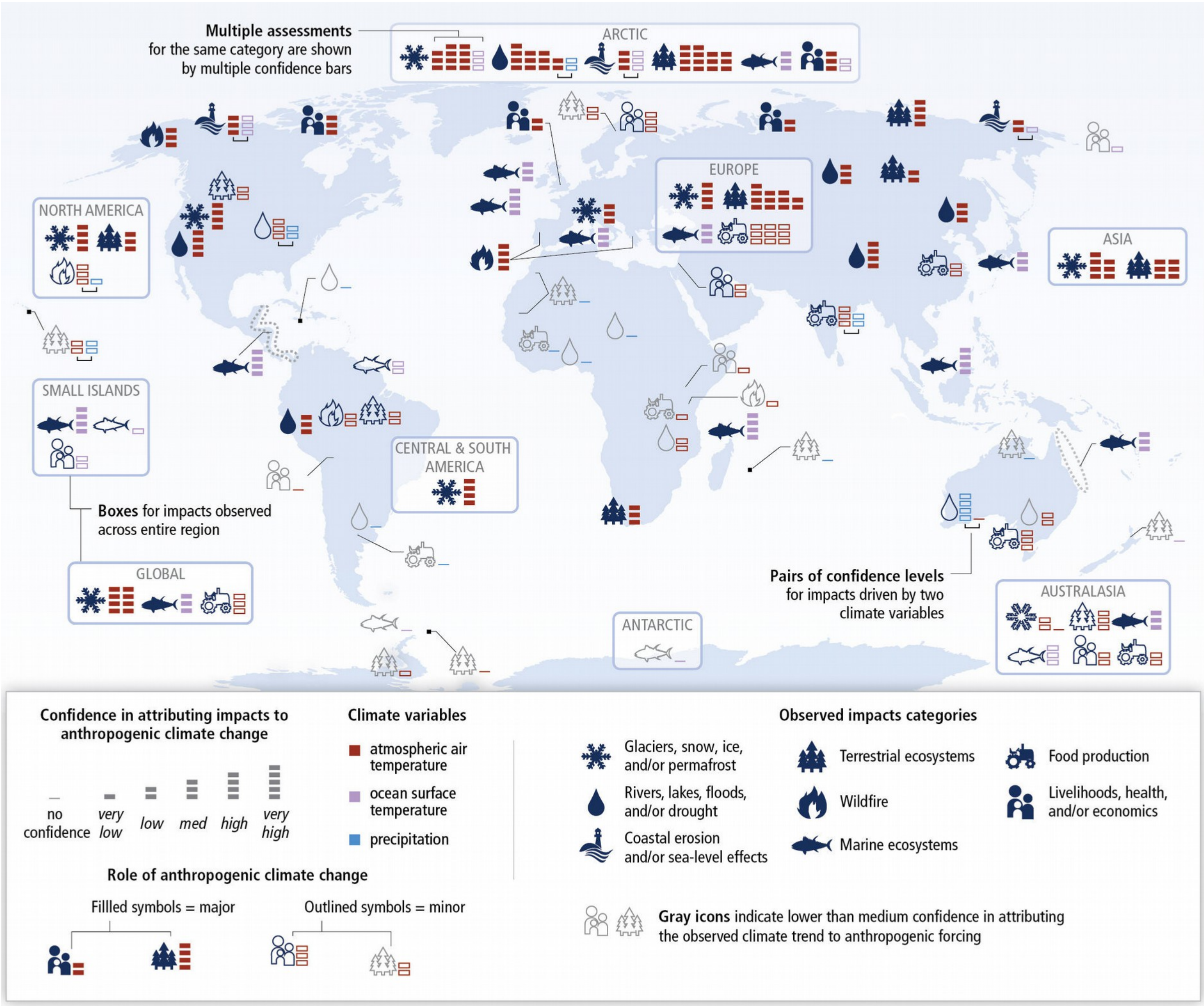


**Figure 5: Observed impacts of anthropogenic climate change for the period 1971-2010. Developed from Figure SPM.2A in IPCC WGII AR5[20], which shows confidence in attributing observed impacts to regional climate trends, irrespective of the cause for those climate trends. Blue symbols indicate impacts where the observed climate trend has been attributed to anthropogenic forcing with at least *medium confidence* in a major or minor role. The confidence bars indicate the combined confidence of the impact and climate attribution step, so confidence can be lower than *medium* for icons in color as a result of low confidence in impact attribution. The respective climate driver is indicated by color of the confidence bars (red: atmospheric air temperature; violet: ocean surface temperature; blue: precipitation). Impacts corresponding to regional climate trends with *no*, *very low* or *low* confidence in attribution to anthropogenic forcing are shown in grey. Low confidence in climate attribution results mainly from lack of monitoring, lack of a clear precipitation response, and inconsistency between the direction of reported trends and trends documented in global observational products over the default period.**

The cryosphere and marine systems feature the highest share of impact cases with at least *medium confidence* of a major role of anthropogenic emissions. In contrast, impacts on the livelihoods of Arctic indigenous peoples are the only such instance within human and managed systems. Still, combined attribution confidence is *medium* for nine of twenty-three temperature-related impacts observed in human systems, albeit the role is usually assessed as being minor. Insufficient monitoring density and a high share of reported impacts driven by precipitation contribute to the low share of attributable impacts in Africa (see also SOM Figure 1, 2). Overall, approximately 56% of the observed impacts are attributed to anthropogenic forcing with at least *medium confidence* in either a minor or major role. This ratio rises to approximately 65% when only evaluating impacts related to temperature.

The AR5 highlights impacts that occur on a continental scale (shown in boxes in Figure 5), i.e. the impact has been observed for the majority of the potentially affected area of the respective world region[6]. Of those continental-scale impacts with a major role of climate change in the observed changes, 76% also have a major role assigned for climate attribution, with 67% yielding *high* or *very high confidence*; for only two values was there *no confidence* in an influence of anthropogenic forcing. These relationships highlight the influence of region size on confidence in climate attribution related to temperature. As can be seen in Figure 6, combined confidence in attribution of impacts to anthropogenic forcing is associated with the spatial extent of the affected area. Approximately 75% of the impacts that occur over very large areas of more than 7.5 million square kilometres are attributed to anthropogenic forcing with *medium* or *high confidence*. In contrast, approximately half of the impacts occurring in regions smaller than 0.5 million square kilometres have *no* or *very low confidence* for the combined assessment.

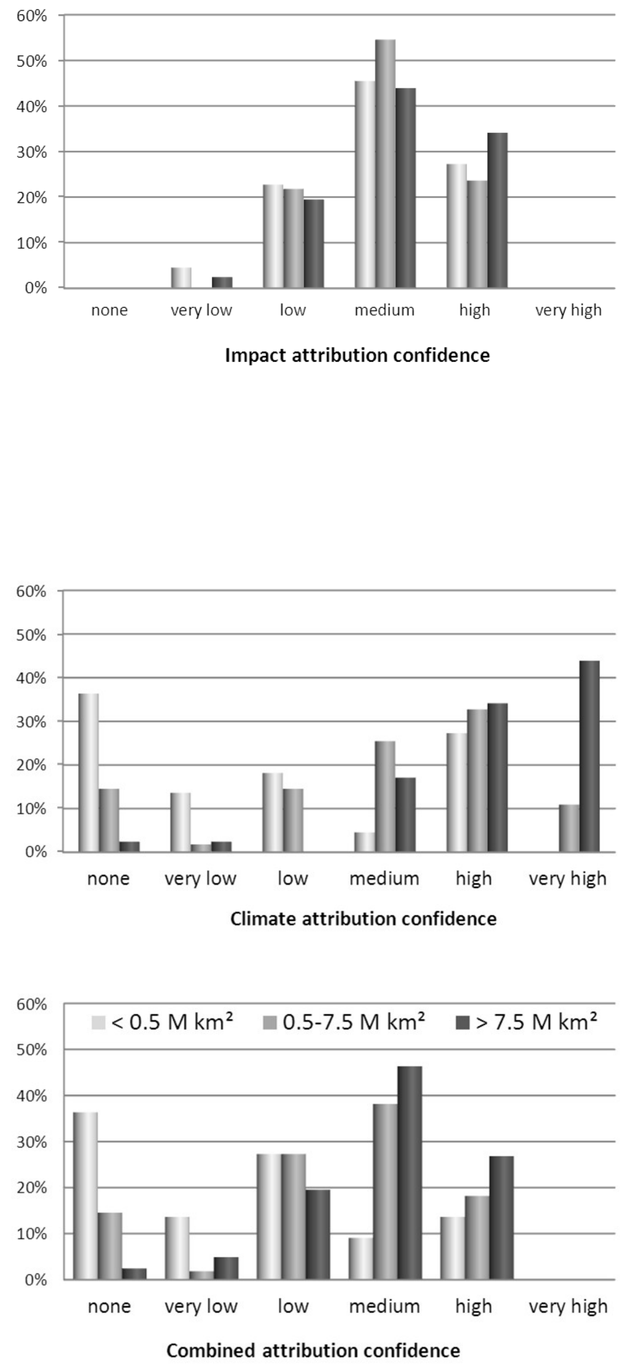


**Figure 6: Normalized distribution of region sizes over attribution confidence levels, for combined attribution confidence (bottom panel), and impact attribution (top) and climate attribution (center) assessments for comparison. Bars indicate the share of assessments within the same region size category that falls into the respective confidence level bin. Regions are grouped into 3 categories, up to half a million square km (left bar), 0.5 to 7.5 million square kilometres (centre bar), and larger than 7.5 square kilometres (right bar).**

## Strengths and limitations

Previous analyses linking observed impacts to climate change have been generic in nature, addressing whether there is an influence of anthropogenic warming on impacts globally, without an inference being possible to individual impacts. Our analysis is the first to bridge these gaps for a large range of impacts, by assessing the role of anthropogenic emissions in each impact individually, including impacts related to trends in precipitation and sea-ice. Examination of evidence along the full causal chain between emissions and specific impacts provides observational support for our understanding of how a variety of systems around the world are being impacted by anthropogenic emissions, contributing to a more nuanced consideration of adaptation options.

By considering uncertainty in observational monitoring quantitatively, the climate attribution algorithm goes beyond most contemporary climate change detection and attribution studies[see 7]. The use of standard global (both observational and climate model-based) data sources facilitates consistency and transparency of the analysis across regions. However, it also neglects other, regional sources of information that may be at least as relevant, such as national observationally-based data products that could be considered in more bespoke analysis. Both fundamental and technical aspects of the construction and implementation of global numerical climate models limit their ability to accurately represent the climate system at some of the regional and local scales investigated here[21]; the algorithm recognizes this limitation, for instance in tuning down confidence for smaller regions and for precipitation. While the formulation of the steps of the algorithm and their resultant confidence factors is fairly straight-forward for some steps, the formulation for other steps and the way the numerical factors are converted to a qualitative scale are more dependent on expert judgement. Steps for which the constraints on their formulation are tighter tend to dominate in determining the final confidence assessment.

This analysis draws from the list of impacts presented in AR5. Most of the investigations informing the AR5 assessment were quantitative, but the development of that list was based on qualitative assessment and included a wide range of sources. That approach ~~has pioneered outreach and~~ allowed for the inclusion of impact categories that were not formally assessed in earlier reports, consistent with recommendations in the literature[22]. However it is subject to issues with expert elicitation, such as limited transparency and the difficulty of calibration. The aggregation level of the listed impacts varies considerably between and within individual regions and sectors; the results should therefore not be misread as a statistical analysis of a representative sample of all impacts. Another important assumption was that a certain level of confidence for the combined effect of two climate variables for an impact also applies to the effect of each climate variable individually.

**Key findings and implications**

This analysis provides the missing link between the observed effects of recent climate change reported in AR5 and the role of anthropogenic forcing of the climate system for the climate trends related to these observations. While it does not comprise detailed, bespoke analyses for each observed impact, in nevertheless provides a robust first assessment of the role of anthropogenic climate change in a wide range of climate-related effects that have been observed around the world. Results confirm earlier statements that anthropogenic climate change is causing discernible impacts on natural systems worldwide, extending the analysis to individual natural systems and to some human and managed systems

Our results clearly link a large majority of the continental-scale, major-role impact attribution assessments highlighted in the AR5 to anthropogenic forcing. However they also demonstrate that neither strong evidence for a specific instance of climate attribution nor strong evidence for impact attribution by themselves necessarily translate into strong evidence for emissions-to-impacts attribution. Most prominently, while AR5 documents a substantial number of significant impacts of long-term trends in precipitation, our analysis indicates that current evidence is often insufficient to link these impacts to anthropogenic climate change.

Despite the benefits of a full examination of the role of anthropogenic emissions in observed impacts, the possibility to perform this investigation is still limited by the high requirements concerning long-term, sustained monitoring of the impact system, the high demand on observationally-based climate products and on models of both the climate and the various impact systems. These factors in turn favour more confident emissions-to-impacts attribution assessments for some systems and regions than for others. Consequently, as noted for impact attribution in the context of the global distribution of observations[23], the absence of observational evidence for an influence of anthropogenic climate change does not imply that impacts are not occurring. Therefore, initiating or recovering observational data for poorly monitored systems and locations constitutes a research priority. Given that confidence in impact attribution is the limiting factor for many cases examined here, the greatest benefit would be gained with an emphasis on monitoring and understanding how human, managed and natural systems respond to climate change.

**Methods**

In this contribution we assess confidence in attributing observed impacts of regional climate trends to anthropogenic forcing of the climate systems. We analyse regionally specific climate trends that have been reported to cause impacts as specified in IPCC WGII AR5[6]. The analysis is based on a novel method assessing the role of anthropogenic forcing in observed changes in climate for specific regions, periods, seasons and climate variables[8]. A confidence algorithm assigns numerical values to a confidence metric as a result of a series of evaluations, expressed as factors on a scale from 0 to 1, that ~~measure~~ represent the adequacy of the input data sources and the agreement between observed and expected climates. The numerical values are then mapped onto the IPCC confidence metric[9] and compared with the corresponding confidence levels for impact attribution. Finally, the impact and the climate attribution steps are combined in a tentative multi-step assessment of the role of anthropogenic forcing for the impact observed. The full analysis comprises the following stages:

- Extracting impact statements from IPCC WGII AR5 Tables 18.5-9 and 18.11;
- Application of selection criteria;
- Identification of the relevant climate variables and seasons for each impact;
- Specification of spatial characteristics for each impact;
- Extraction of corresponding spatially explicit climate data (gridded observational data and climate model output from simulations representing historic and hypothetical 'natural' climates) for the period, season, area and climate variable specified;
- Five steps evaluating the adequacy of the observational and climate model input
- Five steps evaluating the agreement between observed changes and our expectations based on process-based modelling, conducted via a linear regression analysis of the observed datasets against modelled climate responses for the specified climate variable, region, season and period;
- Mapping of the numerical confidence metric arising from multiplying the individual step outcomes onto the qualitative confidence levels; and
- Combination of the impact attribution and climate attribution steps into a multi-step attribution analysis assessing the impact of anthropogenic climate change.

**Selection restrictions, spatial characteristics and default period**

Available data sources do not allow for easy examination of parameters such as ocean acidification, changes in climate variability and sea level rise. Consequently, the analysis was restricted to assessments relating to changes in atmospheric temperature, average precipitation, and ocean surface temperature, the latter also serving as a proxy for sea ice changes in some cases. Selection criteria further included a clearly specified direction of the change in climate (e.g. 'warming', whereas 'changing rainfall patterns' would be excluded) and regional specifications that could be resolved based on ~~the chapter text~~statements in IPCC AR5 WGII[6] and ~~underlying~~ references therein~~literature~~. When more than one climate driver was stated, confidence was assumed to apply to the impact of each driver individually, and the assessment was split into several assessments that were examined individually. The original list of impacts taken from the IPCC AR5 comprises 123 assessments, 25 of them representing impacts influenced by more than one climate driver. Selection restrictions eliminated 19 assessments, resulting in a list of 118 individual impacts after splitting the 13 remaining multiple driver assessments (Supplementary Table S1).

The areas that correspond to an impact are defined by a combination of land-sea boundaries, administrative boundaries, and polygon shapes based on a 0.5° longitude-latitude grid, roughly sketching prominent geographical features where appropriate (see maps in Supplementary Table S2).

We use 1971-2010 as a default period. To test the sensitivity of our results to changes in the period examined, and the respective start and end dates, the climate attribution confidence algorithm was run again using the 1981-2010 and 1971-2000 periods, and for some individual periods that were explicitly stated. The difference between the 40 year period and the 30 year period is small for the attribution of at least a minor role (detection assessment), but becomes larger for the 'attribution of a major role' assessment. As the major role test is based on comparison of the size of the trend against the size of the year-to-year variability, such a result would be expected. With few exceptions, deviation from the default period leads to changes in confidence by one level at most, while the role of anthropogenic forcing stays unchanged. For about half of the tested cases, the outcome of the assessment was not changed at all. Given the survey nature of this assessment, the default period approach can therefore be considered to be robust.

**The climate attribution algorithm**

The climate attribution algorithm assigns a starting value to a metric *c* that depends on the number of data sources available for the climate variable in question ($N_{mod}$: number of models with available simulations, and $N_{obs}$: number of observational data products), with *c* = $\gamma_{source} = \sqrt{Nmod \cdot Nobs}$ .

This value is then left unchanged or reduced based on a series of evaluations, multiplying *c* by a factor γ ≤1 for each step, with maximum penalties varying between 10% and 100%.

$$\text{¿} \cdot \gamma_{physics} \cdot \gamma_{sign} \cdot \gamma_{signal} \cdot \gamma_{ant} \cdot \gamma_{nat} \cdot \gamma_{resid} \cdot \gamma_{major}$$
$$c_m = c \cdot \gamma_{density} \cdot \gamma_{\text{¿}}$$

The resulting value $c_m$ is then converted into confidence levels ranging from '*no confidence*' to '*very high confidence*' via a mapping algorithm. Below, we briefly describe the individual steps, first for the assessment of data sources, then for the comparison between observed and modeled outcomes (regression step). For the detailed formulation and numerical expressions underlying each step, please refer to Stone and Hansen[8].

**Assessment of data sources (evidence)**

**Data sources *c*:** The observational and prediction products comprise the ultimate sources of evidence; the number of such products is thus the starting point for the confidence algorithm. The number of gridded observational data products used in this analysis is three for air temperature [CRU TS 3.22 [24]; GISTEMP v6 (250 km land) [25];UDel v3.01 [26]], four for precipitation [CRU TS 3.22 [24];GPCC v6 [27];NOAA PRECL (1°x1°) [28];UDel v3.01 [26]] and two for sea surface temperature [HadISST1 [29];Hurrell [30]]. Climate model simulations used in the analyses are taken from the CMIP5 climate model database [31] and comprise inputs from the seven climate models used in the IPCC AR5 which have multiple simulations for both "historical" and "historicalNat" scenarios (see Supplementary Table S3for details of the climate models and their simulations used in the analyses).

$\gamma_{density}$: The adequacy of measurement density $\gamma_{density}$ is estimated based on the fraction of variance in the time series for a regional climate variable that is accounted for by the given measurement density, building on the method employed in New et al [32]. The station density information from the CRU TS 3.22 (Harris et al 2014) product are used for land temperature and precipitation and that from the HadSST3.1.1.0 [33,34] dataset for sea surface temperature. Maximum penalty for this step is 100%.

¿ :
$\gamma_{¿}$ Due to the properties of dynamical climate models (limited spatial resolution, limited understanding of smaller scale characteristics) there is a priori less confidence in climate model results for smaller regions. Similarly, the accuracy of observational products becomes more sensitive to the interpolation method used at scales around, or smaller than, the station separation.

To account for this, the confidence metric is reduced by an amount related to the region's size. The functional form is chosen in a way that $\overset{¿}{\gamma_{¿}}$ 1 at continental scales[35] and such that $\overset{¿}{\gamma_{¿}}$ 0.5 at scales around the smallest dynamical resolution of the current generation of climate models (about $4^2$ times larger than the grid cell size[36]). The maximum penalty of 50% acknowledges that the modelling and observational products may retain some skill even if they are not fully resolving processes and features, and that size-related inaccuracies are also likely to emerge as penalties in other tests.

$\gamma_{physics}$: The basic physical processes behind many aspects of the climate are both well understood and mostly resolved in dynamical models, but this is not the case for some variables. For instance, the microphysical processes that generate precipitation are not simulated in climate models but rather approximated by somewhat heuristic algorithms, topographic features important for initiating precipitation are smoothed, and relatively minor shifts in large-scale circulation patterns can have important influences on where precipitation falls. In recognition of this, the confidence metric is reduced by 20% for precipitation.

$\gamma_{sign}$ : In the IPCC WGII assessment[6], impacts are reported to have been caused by a specific observed climate trend. Therefore, in addition to the steps described in Stone and Hansen, it is necessary to confirm that this trend also exists in the observational data sets used in the climate attribution analysis. Reasons for discrepancies include ambiguity over time period, regional or seasonal definitions or disagreement between local and global data sets. This step yields zero should at least half of the observation datasets fail to reproduce the direction of change stated in the AR5.

**Comparison between data sources (agreement)**

The analysis method behind much research carried out in recent years regarding the detection and attribution of climate change to anthropogenic forcing applies a linear regression model to compare output from climate model simulations with observed climate changes [7,37].

If $X_{obs}$ represents variations in an observed regional climate variable as a function of time, $X_{ant}$ represents the expected climate response to anthropogenic external drivers based on climate model simulations and $X_{nat}$ represents the expected climate response to natural external drivers, then the regression equation can be written as (Allen and Tett 1999):

$$X_{obs} = b_{ant} \cdot X_{ant} + b_{nat} \cdot X_{nat} + R \qquad (1)$$

Here R is the residual of the regression and $b_{ant}$ and $b_{nat}$ are the regression coefficients estimated such that the variance of R is minimized. The regression coefficients and their uncertainty due to the limited sampling of the observed climate response against the noise of natural internally generated variability of the climate system are estimated using the code available at http://www.csag.uct.ac.za/~daithi/idl lib/detect/. Traditionally, a response to anthropogenic forcing is considered to be detected if $b_{ant}$ is positive and inconsistent with zero at some level of statistical significance given this sampling uncertainty.

The regression model is estimated separately for each region, and for each combination of the $N_{mod}$ =7 climate models with available simulations and the $N_{obs}$ observational products, that is, for a given region 21 regression models for air temperature over land, 14 for sea surface temperature and 28 for precipitation. Performing these analyses separately ensures that consideration of the diversity of results across input data sources is an important component of the overall assessment. In the interests of both data compression and of focussing on longer timescale variations, 5 year non-running averages of these data are examined. For each of the models with available simulations for estimating the response signals, the sampling noise is reduced by averaging across the 3 to 10 simulations available in each case (see Table S3). The translation of these regression analyses into penalisation of the confidence metric is summarized below. Overall, the penalties emerge from a combination of the fractions of the $N_{mod} \cdot N_{obs}$ regression coefficients that fulfil or fail the test criteria of the respective step and a term that expresses the weight of that step.

$\gamma_{signal}$: This test addresses the question of whether the fingerprint of the anthropogenic response expected by the climate models is found in the observational data. In terms of the regression, the question is whether $b_{ant} > 0$. This step is the critical test for a climate change detection analysis. We multiply the confidence metric by the fraction of the probability distributions for the regression coefficient from each of the $N_{obs} \cdot N_{mod}$ observation-model combinations that is greater than zero, with the maximum penalty being 100%.

$\gamma_{ant}$: A match in magnitude of anthropogenic climate change can be considered an indication that the observed signal analysed in the regression is indeed the predicted signal, rather than, for instance, a response to an ignored driver that happens to closely resemble the predicted response to anthropogenic drivers. Within the regression formulation used here, the question is whether the regression coefficients for the anthropogenic response, $b_{ant}$, are not inconsistent with 1. The maximum penalty is 40%.

$\gamma_{nat}$: The above test only concerns the response to anthropogenic drivers. While they are less directly connected to the conclusions of the analysis, it would also help build confidence (or to maintain it) if the observed response to natural drivers is also not inconsistent with the predicted response. The maximum penalty is 10%.

$\gamma_{resid}$: This test concerns whether the regression is adequate. As an extremely non-linear system, the climate generates variability autonomously, whether it is being influenced by external factors or not. If the assumptions behind the regression hold and all important external drivers have been accounted for, then the residual, R, from the regression should be indistinguishable from this autonomous variability, as estimated from unforced simulations (see Table S3). If the residuals from all $N_{obs} \cdot N_{mod}$ combinations fail the test, then the confidence metric is reduced by 50%. As with inconsistencies in the regression coefficients, gross failure of the residual test is a major concern and could reflect unaccounted drivers.

$\gamma_{major}$ **:** Assessment of the role of anthropogenic forcing in observed changes in climate requires a description of the magnitude of the contribution of human influence relative to other factors[10,38]. We assess whether emissions have had a 'major role' in the behaviour of the observed climate, defining 'major role' as cases where the anthropogenic response accounts for at least one third of the temporal variance. Other possible contributors to the variance would be the response to natural drivers, autonomous variability or possible unidentified drivers.

**Evaluation and combined confidence**

After mapping the resulting value of $c_m$ to the confidence matrix, the major role attribute is assigned if confidence is at least *medium*, else at least a minor role is assigned. Combined confidence is derived from the minimum of the impact and climate attribution roles and confidence levels, respectively. The graphical representation in Figure 5 differentiates the role as follows: Confidence bars depict the combined attribution role and confidence (filled: major; outlined: minor). Impacts associated with a climate trend that has been attributed to anthropogenic forcing with at least *medium confidence* in a major or minor role are highlighted in color. Impacts corresponding to regional climate trends with *no*, *very low* or *low* confidence in attribution to anthropogenic forcing are shown in grey. The respective climate variable is indicated by color of the confidence bars. The full list of impacts with their respective confidence levels can be found in Supplementary Table S1.

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