

Hadley Centre Technical Note 107

Using CMIP6 multi-model ensembles for near real-time attribution of extreme events

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1. Introduction

This technical note presents a system used in the Hadley Centre for the attribution of temperature and precipitation extremes in near-real time. The system employs an unconditional attribution framing, which estimates the changing risk of critical temperature or precipitation threshold crossings under any possible conditions. It adopts a well-established and peer-reviewed risk-based methodology that infers probabilities of extreme events with and without the effect of human influence from large multi-model ensembles of climate model simulations. Applications to the high-impact American heatwave of 2021 and the record-hot European summer of the same year reveal that the likelihood of both events would have been close to zero without anthropogenic climate change, but has been rapidly increasing since the late 20th century. It is shown that by the end of the century such events could occur almost every year under a medium emissions scenario. The system can be applied to ad hoc studies of events as they develop, but may also provide regular assessments of the changing risk of extremes in an operational manner, similar to a forecasting system.

Attribution of weather and climate extremes is a growing area of climate research that quantitatively assesses how causal factors may have altered characteristics of the extremes like their frequency ([Stott et al., 2016](#)). Event attribution places special emphasis on the effect of anthropogenic climate change and has provided strong scientific evidence of its crucial role in recent observed changes in extremes. This evidence underpins a key statement in the latest report of the Intergovernmental Panel on Climate Change (IPCC), asserting that it is now an “established fact that human-induced greenhouse gas emissions have led to an increased frequency and/or intensity of some weather and climate extremes since pre-industrial time, in particular for temperature extremes” ([Seneviratne et al., 2021](#)). The annual special reports by the Bulletin of the American Meteorological Society (BAMS; e.g., [Herring et al., 2021](#)) demonstrate how human influence has been affecting a wide range of extremes around the world, from heatwaves, floods and droughts, to hurricanes, snowstorms, sunshine extremes and more.

Risk-based attribution was introduced by [Stott et al. \(2004\)](#) in their study of the 2003 European summer heatwave and has since become the most popular methodology in event attribution studies. The approach defines extreme events relative to a threshold (e.g., the observed temperature during a heatwave) and utilises large ensembles of simulations with and without anthropogenic forcings to construct probability distributions of the relevant climatic variable in a hypothetical natural world (NAT) and the present (or also future) climate with all external forcings acting on the climate system (ALL). Estimates of the probability of exceeding the threshold (or going below it, e.g., for cold extremes) are then obtained from the two distributions and, by comparing the ALL and NAT probabilities, the anthropogenic influence on the likelihood of extreme events is assessed.

While risk-based studies share the same main concept described earlier, there are

methodological variants that introduce subtle differences in the framing of the attribution question, depending on the way the ALL and NAT ensembles are constructed ([Christidis et al., 2018](#)). In the simplest case, unconditional analyses assess the probability of the event under any possible conditions, typically with data from coupled models that span the entire range of variability. On the other hand, conditional analyses derive the probabilities under certain conditions like the observed state of the ocean (e.g., using atmospheric models), a specific phase of ENSO, or a circulation pattern that was present when the event occurred. Strongly conditioned analyses represent the event more as it happened and are often referred to as “storyline” studies ([Shepherd et al., 2018](#)), while unconditional analyses focus on the risk of crossing an extreme, and often dangerous threshold, which is more relevant in terms of impacts, given that the event will never be repeated in exactly the same way.

The question of whether anthropogenic forcings influence extremes is invariably raised in the aftermath of catastrophic events. Attribution science provides information that can help communities build their resilience, for example, by guiding a more effective design of flood defences, buildings, or transport infrastructure, and making them most suitable for the future climate ([Betts, 2021](#)). It is therefore essential that event attribution is integrated into the framework of developing climate services ([Hewitt et al., 2012](#)). To this end, the Hadley Centre in collaboration with the international research community has been leading the development of prototype attribution services and has also been generating large ensembles of ALL and NAT simulations on a monthly basis with its own attribution system based on the HadGEM3-A model ([Christidis et al., 2013](#); [Ciavarella et al., 2018](#)). The HadGEM3-A system is built on an atmospheric model and hence provides attribution assessments conditioned on the observed state of the ocean. Alongside this development, unconditional analyses have also been produced on an ad hoc basis with coupled model data drawn from large multi-model ensembles of the Coupled Model Intercomparison Project phases 5 (CMIP5, [Taylor et al. 2012](#)) and 6 (CMIP6, [Eyring et al., 2016](#)). Unlike the HadGEM3-A simulations that are extended to near-present every month, the CMIP ensembles already span future decades with different emission scenarios and can thus provide assessments of events in near real-time, as well as complementary assessments of future risks.

The availability of data from model experiments with the latest CMIP6 models makes it possible to produce some basic attribution information, even while events are still developing, at least for certain types of extremes. This early information conveys the overall anthropogenic influence on the likelihood of the event, while detailed studies may subsequently shed more light on the contributions of individual drivers. We have developed a tool that automates the procedure of organising and carrying out unconditional analyses with CMIP6 ensembles and provides users with an assessment of the event within about an hour after the code is set to run. In its initial version this CMIP6 attribution system is only applied to monthly-to-annual temperature extremes over regions large enough to be adequately represented by the models, as these events typically yield the most robust assessments due to their relatively high signal-to-noise ratio. Regional rainfall extremes on similar timescales will also be incorporated into the system during its next development phase. A brief description of the system is given in Section 2 of this technical note, while two

applications to extreme heatwaves in year 2021 are presented in Sections 3 and 4. Some concluding remarks are discussed in Section 5.

2. Data and methodology

2.1. CMIP6 ensembles and observational data

The CMIP6 system uses monthly data from 14 models that provide the necessary experiments for event attribution, namely historical simulations extended to the end of the 21st century with the medium emissions scenario SSP2-4.5 (ALL; [Riahi et al., 2017](#)) and simulations with natural forcings only (NAT) to year 2020. Each model provides several simulations for each experiment and there are in total 82 ALL and 71 NAT model runs for temperature, and similar numbers for rainfall (84 ALL and 73 NAT) as listed in Table 1. The

Table 1. The CMIP6 models used for near-real time attribution analyses. The table gives the number of simulations per experiment and the total multi-model ensemble size (last row) for different variables (temperature and precipitation).

MODEL	T e m p e r a t u r e		P r e c i p i t a t i o n	
	ALL	NAT	ALL	NAT
	hist + ssp245		hist + ssp245	
ACCESS-CM2	3	3	3	3
ACCESS-ESM1-5	18	3	19	3
BCC-CSM2-MR	1	3	1	3
CESM2	3	3	3	3
CNRM-CM6-1	6	10	6	10
CanESM5	25	15	25	15
FGOALS-g3	4	3	4	3
GFDL-ESM4	3	3	3	3
GISS-E2-1-G	3	5	3	5
HadGEM3-GC31-LL	1	4	1	4
IPSL-CM6A-LR	9	10	9	10
MIROC6	3	3	3	3
MRI-ESM2-0	1	3	1	5
NorESM2-LM	3	3	3	3
Total	83	71	84	73

historical and NAT simulations start at year 1850. Regional mean variable estimates averaged over the desired month, season, or combination of months are constructed for every year and converted to anomalies relative to the baseline period 1901-1930 for each simulation. As common in attribution studies, the baseline is set to an early period that is not

heavily influenced by anthropogenic forcings. The ALL distribution for the present climate is then constructed with annual anomaly data in a 20-year period centred at the current year, i.e., a sample of 83×20 anomalies. Similarly, future risks are assessed from ALL data in the last 20 years of the century. As the NAT climate is in the long run stationary, the NAT distribution is constructed using data of all the years of the NAT simulations. The larger NAT samples aid the estimation of commonly smaller probabilities in the natural world (at least for hot extremes). Extreme probabilities are computed with the Generalised Pareto Distribution (GPD), while a simple Monte Carlo bootstrap procedure ([Christidis et al., 2013](#)) is employed for the computation of the sampling uncertainty.

Temperature observations come from a) the CRUTEM datasets for regional analyses ([Osborn and Jones, 2014](#); [Osborn et al., 2020](#)), b) HadCRUT for global analyses ([Morice et al., 2012](#); [Morice et al., 2021](#)), and c) HadUK-Grid for UK analyses ([Hollis et al., 2019](#)). Extension of the system for attribution of rainfall extremes will utilise data from the CRU TS4 dataset ([Harris et al., 2020](#)). The observations are used firstly to evaluate the models and, secondly, to set the threshold for the definition of extreme events.

2.2. Model evaluation

The methodology used by the multi-model CMIP6 attribution system has been peer-reviewed and applied to several published studies of extreme events, including the record hot May of 2021 in Western Europe ([Christidis and Stott, 2022](#)), the 2018 summer heatwave in the UK ([McCarthy et al., 2019](#)), the wet winter of 2019/2020 in the UK ([Davies et al., 2021](#)), etc. It is essential that when an attribution analysis is carried out, it also includes evaluation tests of the models employed, to ensure that they can represent well the type of extreme event under consideration in the reference region. The simplest qualitative assessment would be an illustration of the modelled historical timeseries of the relevant variable (e.g., regional summer temperature anomalies, for the case of a summer heatwave) plotted together with the observations over their common period. Such an illustration can easily flag up instances when models do not reproduce well observed trends or variability.

Taking a step further, a set of standard evaluation tests have been introduced to assess more formally whether the models are fit-for-purpose ([Christidis et al., 2020](#)). These tests evaluate the ensemble as a whole, rather than considering models individually. However, they can still identify cases where individual models may demonstrate a different behaviour from the rest of the ensemble, so that such models may be removed if necessary. The most instructive tests include a) an assessment of trends that checks whether the observed trend falls within the range of the simulated ones; b) a power spectra analysis that checks whether the modelled variability is consistent with the modelled variability; c) a quantile-quantile (Q-Q) plot that checks whether different parts of the distribution (main body and tails) are realistically represented by the ensemble. Examples of these evaluation tests will be given in the presentation of the two case studies in Sections 3 and 4.

2.3. Python software

The CMIP6 attribution tool has been developed in Python and the code is structured on four main routines that are called in sequence by a driving script. These include the following:

- The inputs section. This part of the code needs to be edited by the user to define the details of the analysis. The user can specify here the month, or combination of months required (e.g., June-July-August for a European summer heatwave event), the year of the event under consideration (e.g., present year, for real-time analyses), the coordinates of the region (latitude-longitude boundaries), and the threshold for the definition of extreme events. If no threshold is specified, the code sets it to the maximum record in the observations.
- The data processing section. This routine accesses the netcdf files with the input temperature data, re-grids the modelled fields on the observational grid and masks them so that they have the same coverage with the observations. It also extracts the analysis region, and, for every year, it computes the regional mean anomaly averaged over the month, or combination of months, as required. The resulting timeseries of observed and simulated anomalies are saved as numpy arrays.
- The evaluation section. This is the part of the code that produces a graphical representation of the model evaluation tests. It includes a plot with observed and modelled timeseries of the relevant variable from the observations and the ALL and NAT experiments, an illustration of the individual ALL trends over the observational period together with the observed trend, an illustration of the power spectra analysis, and finally a Q-Q plot for a basic assessment of the distribution.
- The attribution outputs section. This section provides probability estimates for extreme events in the NAT climate, the climate when the actual event took place, and the climate of the late 21st century. There are 1000 estimates for each of the three probability outputs that can be used to derive the associated 5-95% uncertainty range. The output probabilities are saved in numpy arrays and the best estimates together with the uncertainty range are also saved in a text file.

3. Example 1: The American heatwave in June 2021

A real-time attribution study with CMIP6 multi-model ensembles was conducted during the devastating heatwave that affected large parts of North-western America from late June through mid-July 2021¹. The event was linked to a heat dome², an area of persistent high pressure that remained stationary over several weeks trapping warm air underneath. The extreme heat led to loss of life and sparked wildfires in vast parts of Canada. Given the

¹ <https://www.metoffice.gov.uk/about-us/press-office/news/weather-and-climate/2021/2021-european-summer-temperature-impossible-without-climate-change>

² <https://www.rmets.org/metmatters/what-heat-dome>

unprecedented intensity of this event and its impacts on society, there is a clear policy need to understand to what extent climate change played a role and whether similar events could become more frequent in future. Similarly, there is a large public demand for information, as evident in the extensive media coverage of the Hadley Centre attribution study, which includes reports and interviews by the BBC, CNN, Bloomberg, Reuters, the Guardian and several other national and international news outlets.

In mid-June 2021 it became evident that the month would most likely become the warmest on record in the heatwave-affected region and an attribution analysis was set up to examine the likelihood of breaking the previous June record (in 2015), with and without the effect of human influence on the climate. The simulated June temperatures come from 58 ALL and 64 NAT simulations generated by 11 CMIP6 models. The analysis employed smaller ensembles than shown in Table 1, as some model data had not become available yet. Observed and modelled timeseries of the June anomalies averaged over the reference region (104-130W, 32-50N) are illustrated in Fig. 1. Both CRUTEM4 and the ALL experiment suggest a steep increase in temperature since the late 20th century that continues throughout the 21st century (under SSP2-4.5), expected to steadily increase the likelihood of extremely hot months. Such long-term warming is not seen in the NAT climate, suggesting it is of anthropogenic origin.

Results from the model evaluation tests are shown in Fig. 2. The observed June temperature trend is well within the range of the ALL simulations (top panel) and in close agreement with the ensemble mean. Power spectra also indicate good consistency between the models and CRUTEM4 (middle panel). The Q-Q plot produced for each simulation separately shows lines that lie close to the diagonal, which indicates that the modelled distribution compares well with the observed one. Hence, on the basis of this assessments, the models are deemed suitable for an attribution analysis of the heatwave.

Probabilities of a new June temperature record in the region are computed next. The 2015 anomaly of 3.5 °C (previous record) is set as a threshold to define extreme events. Return time estimates (inverse probabilities) and their associated uncertainty are reported in Table 2. It is found that a new record in the region would have been almost impossible in the NAT world, but is now relatively common (return time of about 15 years) and, under SSP2-4.5, the threshold is set to be crossed almost every year. This rapid increase in the likelihood of extremely hot months under the effect of human influence reflects a rapid shift in the climate of the region and stresses the need for effective adaptation planning.

Table 2. Attribution results. Return time estimates for extremely hot events in the North-western American region considered in the analysis. The 5-95% uncertainty range is given in brackets.

	Return Time (years)
NAT Climate	thousands of years
Present Climate	15 (13 to 18)
End of 21 st Century	1.49 (1.44 to 1.54)

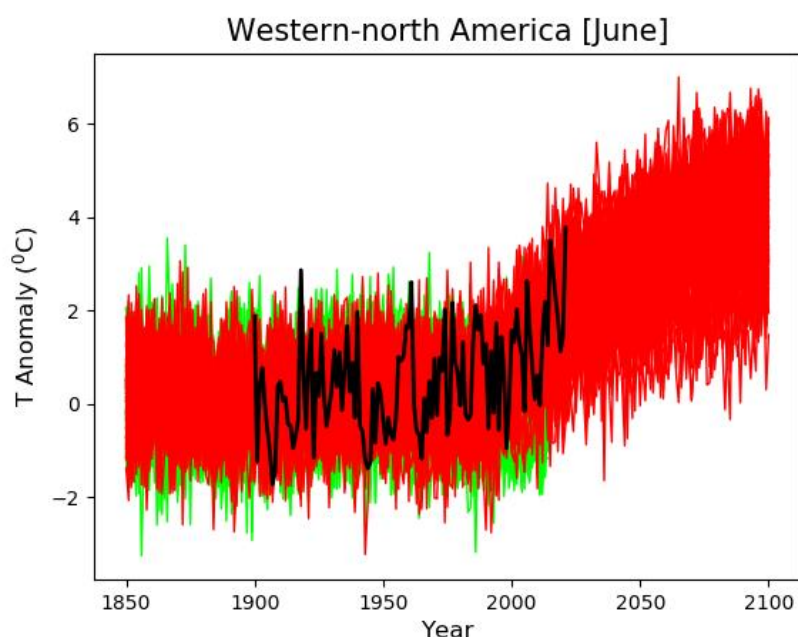


Figure 1. Timeseries of the June temperature anomaly (relative to 1901-1930) in the reference North-western American region computed with observational data from CRUTEM4 (black line) and the CMIP6 ALL (red lines) and NAT (green lines) simulations.

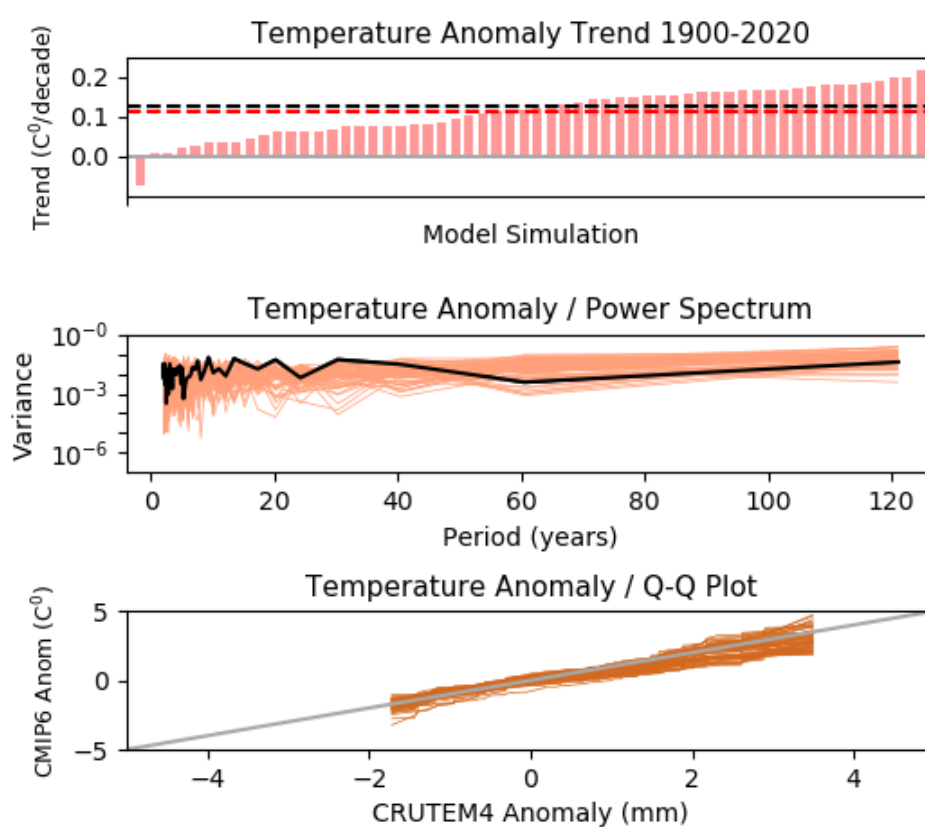


Figure 2. Evaluation of the CMIP6 models. Top panel: temperature trends over the observational period computed with CRUTEM4 (black dashed line) and individual ALL simulations (vertical bars). The dashed red line marks the ensemble mean. Middle panel: Power spectra from CRUTEM4 (black) and the ALL simulations (orange). Bottom panel: Quantile-Quantile plot for each of the ALL simulations.

4. Example 2: The record summer temperature of 2021 in Europe

A second application of the CMIP6 attribution system examined the effect of human influence on the record summer temperature of 2021 in Europe, which was close to 1°C above the 1991-2020 average³. Extreme heat in the Mediterranean region led to locally record-breaking maximum temperatures and devastating wildfires in Greece, Turkey and Italy that caused loss of life and livelihood and destroyed large forest areas. The study provided compelling evidence of anthropogenic climate change being the key driver of the event, which again provides important information from a policy perspective in helping to understand current and future climate risk. The potential impact of this information in helping the public to understand the risk of climate change was also demonstrated by the significant media interest the study gained. Main findings were highlighted on BBC's Panorama programme and achieved 701 pieces of media coverage, ranging from the front page of the Guardian and i newspapers, to online regional news outlets and ITV's Good Morning Britain.

The analysis uses the ensembles shown in Table 1 (83 ALL and 71 NAT simulations) and sets out to quantify the likelihood of having a new summer temperature record in year 2021. Extremes are therefore defined as exceedances of the previous record in year 2010, an anomaly of 2.34 °C relative to 1901-1930. Summer mean temperatures are computed from the monthly values in June, July and August for each year and averaged over the European region 10W-60E, 36-72N. The observed and simulated timeseries in Fig. 3 suggest that European summers have become almost 2 °C warmer and this warming is projected to double during the course of the century under SSP2-4.5. Such a temperature rise is not present in the NAT climate, which again indicates that it is driven by human influence. Model evaluation tests (Fig. 4) show that the models represent well the observed European summer temperature trend (top panel), the temperature variability (middle panel) and the distribution of historical anomalies (bottom panel).

Attribution results are summarised in Table 3. Hot summers like those experienced in Europe in recent years have a near-zero probability in the natural climate but are now common and estimated to occur every 2-3 years at present, and every year by the end of the century. This implies that as summer temperatures continue to rise sharply, new records are bound to be set on a regular basis, and summers that were considered extremely hot in the pre-industrial world, are quickly becoming common, or even cool in our warming climate. The speed of change in the likelihood of extremes is depicted in the timeseries of their return time shown in Fig. 5. Consistent with previous work (Christidis et al., 2015), the study shows a striking increase in the likelihood of extremely hot summers since the late 20th century, which, in turn, increases the vulnerability of European citizens to severe heatwave impacts.

³ <https://www.metoffice.gov.uk/about-us/press-office/news/weather-and-climate/2021/2021-european-summer-temperature-impossible-without-climate-change>

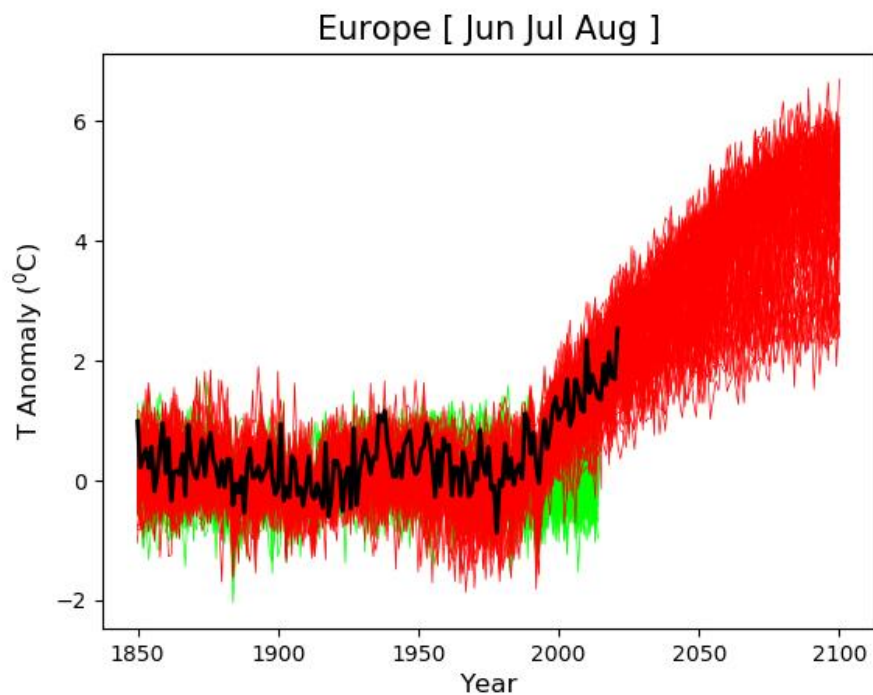


Figure 3. Timeseries of the summer temperature anomaly (relative to 1901-1930) in Europe computed with observational data from CRUTEM4 (black line) and the CMIP6 ALL (red lines) and NAT (green lines) simulations.

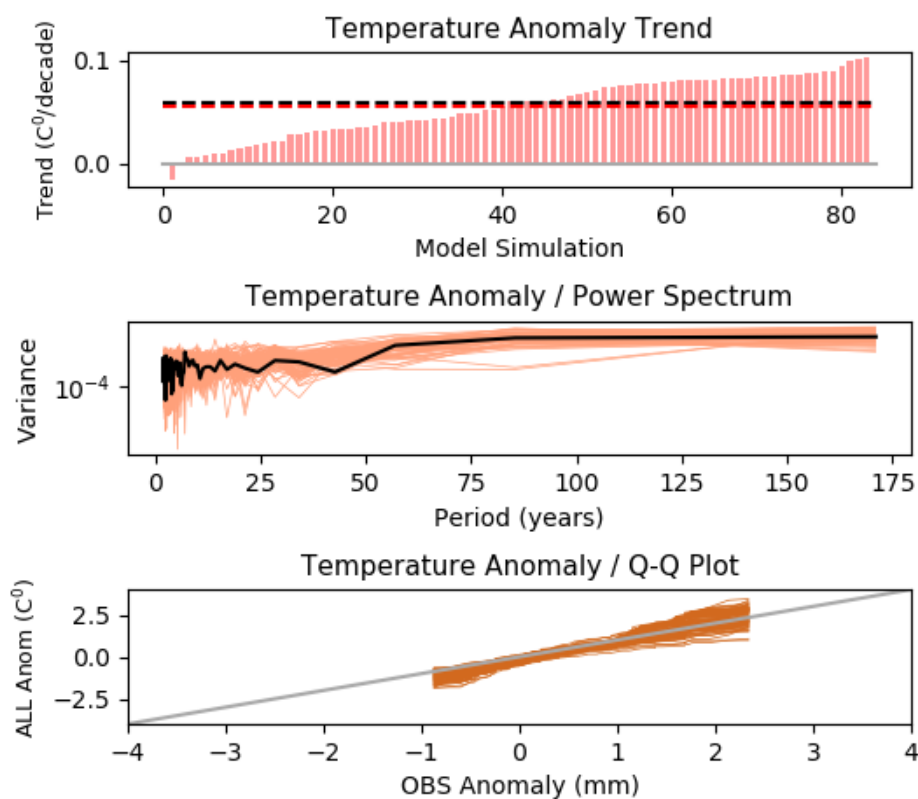


Figure 4. Evaluation of the CMIP6 models. Top panel: temperature trends over the observational period computed with CRUTEM4 (black dashed line) and individual ALL simulations (vertical bars). The dashed red line marks the ensemble mean. Middle panel: Power spectra from CRUTEM4 (black) and the ALL simulations (orange). Bottom panel: Quantile-Quantile plot for each of the ALL simulations.

Table 3. Attribution results. Return time estimates for extremely hot summers in Europe. The 5-95% uncertainty range is given in brackets.

	Return Time (years)
NAT Climate	thousands of years
Present Climate	2.80 (2.67 to 2.95)
End of 21 st Century	1.02 (1.01 to 1.03)

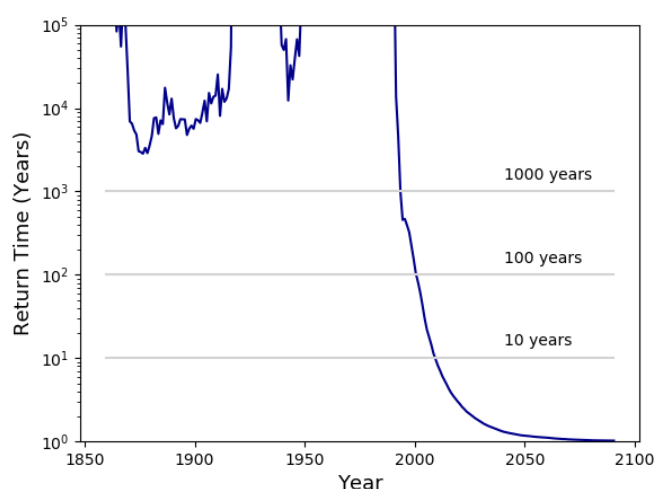


Figure 5. Timeseries of the return time of extremely hot summers in Europe computed with data from the ALL ensemble in 20-year rolling windows.

5. Discussion

The CMIP6 multi-model ensemble system presented in this technical note facilitates simple unconditional attribution assessments to be made while extreme events are still developing. The system is currently set up to assess temperature extremes on regional and global scales and will next be extended to enable analyses of precipitation extremes on similar spatial scales. An upgrade to the latest CRUTEM5 and HadCRUT5 observational datasets will also take place in all future applications. Some main uncertainties in the methodological approach have been addressed. For example, the effect of sampling uncertainty has been quantified, while modelling uncertainty is to some extent addressed by the use of several different models that have been evaluated against observations. There are of course known caveats, like for example the inhomogeneity of the ensembles with some models contributing more simulations than others, or the scenario uncertainty in future projections, but despite these limitations, and on the basis of the model evaluation assessments, the method is expected to provide reliable estimates of changes in the likelihood of extremes and of its associated uncertainty.

While the CMIP6 system offers useful and timely attribution information, it should be stressed that this information is only a single perspective of the overall effect of anthropogenic climate change that does not explain every aspect of the event. It is therefore important that more detailed, follow-up analyses bring in complementary perspectives and investigate, for example, extremes on local scales (e.g., cities) and of shorter duration (e.g., over days), the role of atmospheric circulation (e.g., blocking systems), prevalent modes of large-scale variability (e.g., ENSO phases) and prevalent oceanic conditions, as well as impacts linked to the event (e.g., wildfires or heat-related mortality) etc. A synthesis of all this information would provide a more complete picture and understanding of the event, but as such focussed studies commonly become available months (or even years) later and are generally tailored to the specifics of each event, they are more difficult to be integrated into an operational attribution framework. On the other hand, the CMIP6 system can not only be applied to ad hoc events, like the case studies presented earlier, but , similar to a forecasting system, it may also become part of a regular service, reporting estimates of the changing risk of certain types of extremes on a monthly or seasonal basis.

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