Explaining Extreme Events of 2020 from a Climate Perspective

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EXPLAINING EXTREME EVENTS OF 2020 FROM A CLIMATE PERSPECTIVE

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Cover: Low water bathtub ring on sandstone cliffs around Lake Powell in Glen Canyon National Recreation Area in Arizona. (credit: trekandshoot/Shutterstock.com)

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The Life and Times of the Weather Risk Attribution Forecast

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The Weather Risk Attribution Forecast (WRAF) provided a testbed for proactive estimation of the human role in extreme monthly events. This paper looks back on issues that the WRAF highlighted.

In the 2000s, a few studies had demonstrated the potential for evaluating the role of anthropogenic emissions in specific observed weather and climate events (Stott et al. 2004; Hoerling et al. 2007; Yiou et al. 2007; Jones et al. 2008; Perlwitz et al. 2009). Researchers involved in such studies were wondering if these methods could be developed into operational services that would provide an assessment in close to real time (Stott and Trenberth 2009; Stott and Walton 2013). However, research focused on further tests and development of the analysis methods because they were still poorly understood (Otto et al. 2012), leaving creation of operational services until a later date.

We identified a drawback of this approach. While at some time in the future event attribution researchers would supposedly become confident in their attribution methods for evaluating the anthropogenic role, they would have to further their understanding and capabilities to deploy these methods in an operational process (National Academies of Sciences Engineering and Medicine 2016). As a research institute without operational responsibility, the University of Cape Town did nevertheless have expertise in regular provision of climate services, in particular a seasonal climate fore-
cast (Browne Klutse et al. 2016). This provided a suitable environment for developing and testing a prototype operational event attribution service: expertise in climate service provision, no official liability for trying things out, a seasonal climate forecast system to serve as the engine, and expertise in event attribution research (Angélil et al. 2014; Wolski et al. 2014). Hence there was an opportunity to gain experience with quasi-operational production of event attribution information that could be shared with other institutions throughout the world that were considering to develop operational services at a later date. An additional motivation was a possibility that event attribution services would be particularly useful in the African context in terms of monitoring losses and damages to climate change.

With these motivations in mind, we developed the Weather Risk Attribution Forecast (WRAF) system to provide information about the human role in extreme events at the monthly scale (Lawal et al. 2015). The WRAF was designed as a proactive system that would calculate event attribution metrics before the occurrence of the events, with the realization that most analyzed events would never materialize. There were four main objectives:

1) to demonstrate the feasibility of a global proactive event attribution system;
2) to gain experience with the usage of a proactive event attribution service;
3) to share lessons from that experience with other institutions; and
4) to provide a preliminary attribution information service.

In this paper we will discuss how these objectives shaped the development of the WRAF, and how successfully it responded to each.

**Design.**

A proactive event attribution system, one that performs calculations before any event, could be formed by tying it to an existing seasonal forecast system. The WRAF followed from a then-new method for using simulations of an atmospheric model for event attribution evaluation (Pall et al. 2011) and applied it to the University of Cape Town (UCT) seasonal forecast system. This seasonal forecast comprised a 10-member initial condition ensemble of the HadAM3P-N96 atmosphere–land model (Jones et al. 2004) run at 1.875° × 1.25° horizontal resolution with observed greenhouse gas concentrations and other radiative forcings. The first month (which we refer to as the hindcast) was driven with observed sea surface temperatures (SSTs; Reynolds et al. 2002), with subsequent months driven by a continuation of the seasonal anomaly from that first month added to the seasonal climatological SSTs; although the simulations extended out an additional three months, we used only the first month with fully forecast SSTs (2 months after the first month) as our forecast period. This persistent-anomaly forecast of SSTs was skillful for the primary oceanic influences on southern African climate, in particular El Niño–Southern Oscillation (ENSO) and the Indian Ocean dipole (Jury et al. 2004), because they tend to vary slowly on monthly to seasonal time scales (Ratnam et al. 2020; Ren et al. 2019). We found no systematic difference between results using the forecast month (with fully forecast SSTs) or hindcast month (with observed SSTs). Attribution estimates for the chance of an unusually hot, cold, wet, or dry month based on the forecast period were posted immediately after completion of the forecast simulations, and updated with replacement estimates three months later based on the hindcast month of the new simulations. In this paper we present sample results produced under the hindcast (observed SST) conditions covering January 2009 through 2011 because we produced additional simulations (a total of 60 per scenario) for this period and hindcast setup. The forecasts were compared to a set of naturalized counterfactual forecast simulations, inspired by previous factual–counterfactual comparisons. Following Pall et al. (2011), we surmised that interest would tend to be in the effect of anthropogenic greenhouse gas (GHG) emissions rather than of all anthropogenic interference. A parallel “non-GHG” forecast explored this effect by rerunning the seasonal
forecast but with greenhouse gas concentrations reduced to preindustrial levels and the SSTs cooled according to a spatially and seasonally varying estimate of the historical warming attributable to anthropogenic emissions based on the HadCM3 atmosphere–ocean model (Pall et al. 2011).

Results were issued monthly online (now available at http://climate.web.runbox.net/wraf/), with calculations for unusually hot, cold, wet, and dry monthly averages across 58 terrestrial regions of about 2 million km² size (Stone 2019). We only considered monthly averages because of existing support for HadAM3P-N96’s general performance at monthly time scales and to keep assessments to a manageable number of cases. Figure 1 shows how changes in greenhouse gas concentrations altered the chance of an unusually hot and an unusually wet June 2011 in each of the 58 regions (unusually cold maps and dry maps not shown). The question was how have emissions altered the chance of exceedance of the 90th percentile for Junes in historical simulations for all prior years starting in 1960. Calculations were based on Gaussian fits to the 10 (or 60) member ensembles with results categorized according to what could be said with confidence.

Greenhouse gas role in unusually hot June 2011

![Map showing the chance of unusually hot June 2011](image)

- **Chance is at least halved**
- **Chance is at least smaller**
- **No detectable difference**
- **Chance is at least doubled**
- **Chance is at least larger**

Greenhouse gas role in unusually wet June 2011

![Map showing the chance of unusually wet June 2011](image)

- **Chance is at least halved**
- **Chance is at least smaller**
- **No detectable difference**
- **Chance is at least doubled**
- **Chance is at least larger**

Fig. 1. The attribution hindcast (i.e., using observed SSTs) issued for June 2011 for the effect of anthropogenic greenhouse gases on the chance of (top) an unusually hot month and (bottom) an unusually wet month in each of 58 regions, using 60 simulations per scenario (issued in August 2011).
Selection bias.
Selection bias poses a major challenge for event attribution analysis (Chase et al. 2006; Christiansen 2015): conclusions can be influenced by selection or definition of extreme events based on event occurrence or by assumptions about causes of their occurrence. For instance, in a synthesis setting it may be relevant if attribution of the cold events that did not occur is not considered, simply because these events hardly ever occur now. The WRAF’s proactive operation was specifically designed to minimize post hoc selection bias, by ignoring whether events had occurred. However, in the end we have concluded that selection bias is an innate feature of any operational event attribution service. Anecdotally, we and others (e.g., conference attenders) found that we could still justify consideration of neighboring regions (when trialing with smaller regions), neighboring months, or the same month from other years. Attempts to circumvent this only made the analysis less relevant, for instance outputting to enormous 10 million km$^2$ regions did not capture colloquial extreme events (Stone 2019). More importantly, selection inevitably occurred through the public communication of conclusions: no one was interested in assessment of events that had not occurred. Nevertheless, we did conclude that proactive services have an application in synthesis monitoring of changing climatic hazard (Risser et al. 2017).

Categorization.
WRAF conclusions were expressed in terms of categories describing what we could say with confidence, for instance that greenhouse gas emissions had “at least doubled” the chance of the event. In our experience this was a successful communication format in the sense that the conclusion seemed to be accurately interpreted by audiences we interacted with. However it did have some quirks. Figure 2 shows the frequency at which each category was assigned to each region over a 36-month period, for unusually hot and unusually wet months. While tropical regions were classified as red (“chance is at least doubled”) in almost all of the 36 months, the northern high-latitude regions were only classified as such about half of the time. In fact the estimated most likely risk ratios tended to be similar (considerably greater than 2) for the tropical and high-latitude regions, but the higher endogenous month-to-month variability in northern high-latitude regions during winter produced a broader confidence interval and hence less frequent allocation of the confidently “at least doubled” category (and even of the “at least increased” category) (Risser et al. 2017).

Question of demand.
A number of possible users of event attribution information had been identified by the research community around the time of the start of the WRAF project, including a test bed for improving our understanding of the climate system, a response to public demand during the occurrence of events, evidence for litigation, insight into adaptive capacity and adaptive needs, monitoring of geoengineering efforts, and support for more adaptive insurance (Stott et al. 2013). Two of these could be particularly relevant for Africa: event attribution information could inform international loss and damage claims, by demonstrating whether “dangerous anthropogenic interference with the climate system” had occurred within African territories; event attribution information might be used to monitor the actual degree of climate resilience achieved, supporting the strong interest that African economic development should be resilient to plausible future climate change. We did not actively engage with potential non-research audiences, but interest in African-specific applications seemed limited during the course of the project, in part because the concept of reparation for attributable losses and damages runs counter to a policy of supporting general sustainable development in Africa (Huggel et al. 2016; Parker et al. 2017). We also had some anecdotal experiences that suggested that evidence produced by African institutions would not be considered as credible.
Legacy.

After seven years, the WRAF ceased operation with the March 2017 attribution forecast. Most pressingly, UCT was ceasing its seasonal forecasting product, meaning the WRAF would have to be a stand-alone activity. More generally, the WRAF had achieved its original objectives, through demonstration and experience of a proactive event attribution system, and sharing that experience in such venues as the international Attribution of Climate Events (ACE) series of workshops (Stott and Walton 2013; Stott et al. 2013) and a major report on the status of event attribution science (National Academies of Sciences, Engineering, and Medicine 2016). These contributions helped inform the first generation of event attribution services at mandated institutions around the world, and thus reducing the requirements for further testbeds.

Perhaps ironically, one of the main contributions of the WRAF was in highlighting how event attribution research was hindered by the lack of data products designed specifically in support of that research. This led to the International CLIVAR C2OC+ Detection and Attribution project (Stone et al. 2019), a multi-institution, multimodel effort to produce petabytes of climate model data for event attribution research, which is based on many of the protocols developed and tested on the WRAF test bed. Although it is no longer running, the legacy of the WRAF is visible in a number of research and service activities around the world.

Fig. 2. Maps showing the frequency of categorization for unusually hot months and unusually wet months during the January 2009 through December 2011 period. These particular plots are based on the hindcast (observed SSTs) simulations, during three years with 60 simulations per scenario.
Acknowledgments. Development and operation of the WRAF was supported by Microsoft Research, the South African Water Research Commission under contract K5-2067, and the Director, Office of Science, Office of Biological and Environmental Research of the U.S. Department of Energy under Contract DE340AC02-05CH11231. Knowledge transfer was also supported by the U.S. National Oceanic and Atmospheric Administration’s Climate Program Office; the International Meetings on Statistical Climatology; the U.K. Foreign and Commonwealth Office; and the World Climate Research Programme. This paper was written with support from the Endeavour Whakahura project of the Ministry of Business, Innovation and Employment of Aotearoa New Zealand. We thank two reviewers for their help in improving the manuscript.

Data availability statement. Data from the WRAF are available from the C20C+ D&A project’s archive at https://portal.nerc.gov/c20c/data.html, under the UCT-CSAG/HadAM3P-N96/All-Hist/est1/v1-0 (forecast/hindcast) and UCT-CSAG/HadAM3P-N96/NonGHG-Hist/HadCM3-p50-est1/v1-0 (naturalized forecast/hindcast) labels.

References


Subseasonal to Seasonal Climate Forecasts Provide the Backbone of a Near-Real-Time Event Explainer Service

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The Bureau of Meteorology serves the Australian community to reduce its climate risk and is developing a suite of tools to explain the drivers of extreme events. Dynamical sub-seasonal to seasonal forecasts form the backbone of the service, potentially enabling it to be run in near real time.

The Australian Bureau of Meteorology (BoM) provides forecasts at daily, multiweek, and seasonal time scales along with a range of other services. Customers are keen to be informed about the causes of extreme weather and climate events to help them in their planning and decision making. While attribution is often framed in terms of understanding the role of climate change, it is also useful to understand the role of climate variability and circulation changes in causing extreme events (e.g., Mindlin et al. 2020). The focus of the Event Explainer is to reduce climate risk by informing decision makers about the causes of extreme events and, if there are persistent underlying drivers, the event’s likelihood of recurrence over the coming season or decade.

This article describes the tools that are being developed at the BoM to explain the causes of extreme weather and climate events, and how those tools would add value to existing services. The novel aspect of the tools is that they will link with the dynamical sub-seasonal to seasonal (S2S) forecasts currently in operation. Thus, operational staff are alerted to the upcoming extreme event, and have time to diagnose and quantify
the causes, thereby facilitating earlier and more effective communication with the public and stakeholders and potentially tailoring the service to users’ needs. Hence there is strong appeal in using an operational forecast system as the backbone of a real-time attribution system.

**Tools being developed for the Event Explainer.**

We propose using a suite of applications for the Event Explainer service to enhance the benefits that can be drawn from different approaches and increase confidence in the final messages (Philip et al. 2020). Initially, regional heatwaves will be the focus of the BoM’s attribution service, but the techniques can be used to explain the causes of other extremes, including the circulation changes associated with high-intensity rainfall or fire weather. The applications are still under development and the skill of the techniques will be tested for each type of event, and any relevant caveats will be considered.

To illustrate the methods described here we apply the preliminary developmental versions to the heatwave preceding the “Black Saturday” fires over southeast Australia in late January and early February 2009 (see Fig. 1a) (Bureau of Meteorology 2009).

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**Fig. 1.** Application of developmental versions of the Event Explainer methods to the heatwave period preceding Black Saturday fires in late January and early February 2009. Temperature anomalies 27 Jan–8 Feb 2009 from (a) ERA-Interim (Dee et al. 2011) and (b) ACCESS-S1 forecasts initialized on 17 Jan 2009 and (c) the present-day forecast minus the same forecast on a low CO₂ background mean state. (d) CMIP5-based (Taylor et al. 2012) distributions of average January daily maximum temperature for Victoria from the present climate (orange: 2006–26, RCP8.5) and natural-forcing only simulations (blue: 1985–2005), based on the method of Lewis et al. (2014). The observed January 2009 anomaly (Jones et al. 2009) is shown as a vertical black line. (e) January 2009 loading values from a multiple linear regression (MLR; 1979–2019) of known drivers of Victorian climate in January. Drivers include (from the right) detrended indices of the southern annular mode (SAM; http://www.nerc-bas.ac.uk/icd/gjma/sam.html), Niño-3.4 (Reynolds et al. 2002), antecedent seasonal rainfall (Jones et al. 2009), and the trend (years). The reconstructed anomaly in January 2009 is primarily driven by the trend, with some contribution from the moderate La Niña.
Modified initialization S2S Prediction Attribution (SPA) method. In the BoM's Research section, scientists developed a system to quantify the influence of increasing levels of greenhouse gases on extreme events using an initialized global dynamical coupled ocean–atmosphere S2S climate prediction system (Wang et al. 2021). In a series of case studies, the system was applied to quantify the influence of carbon dioxide increases since ~1960 on several Australian events:

- heat events on a subseasonal time scale (Arblaster et al. 2014; Hope et al. 2015, 2016);
- fire weather over two weeks in 2017 (combining the zero-lead forecast with observed antecedent rainfall and cooler (minus 1°C) antecedent temperature observations to define the drought factor) (Hope et al. 2019);
- extreme monthly rainfall and associated circulation changes (Hope et al. 2018);
- frost events in southwest Australia and circulation (Grose et al. 2018); and
- extreme dry conditions in Tasmania (Grose et al. 2019).

As this approach uses initialized forecasts, there was a potential interest in the benefit that the attribution system could be used to describe the influence from increasing greenhouse gases prior to the event occurring [presented at the 2018 annual meeting of International Detection and Attribution Group (IDAG) in Berkeley, California]. At the time, the approach used the BoM’s low-resolution operational S2S forecast system POAMA, presenting the option of running attribution experiments alongside the operational forecast service. Since then, a major operational upgrade has provided an opportunity to use a much higher-resolution coupled model with advanced physics, the Australian Community Climate and Earth-System Simulator subseasonal-to-seasonal prediction system (ACCESS-S; Hudson et al. 2017). Development is now underway to assess the skill and utility of ACCESS-S as a tool for attribution. A preliminary forecast experiment of the Black Saturday heatwave has been performed using an early version of the ACCESS-S system, ACCESS-S1. The ensemble mean ACCESS-S1 forecast reasonably captured the temperature anomaly pattern during 27 January–8 February 2009 over southeast Australia from 17 January 2009 (i.e., 10-day lead time (Fig. 1b). In comparison to the forecast with the present level of CO₂, a set of ensemble forecasts was generated for the same event but under the low CO₂ climate conditions of the early twentieth century, with CO₂ set to 297 ppm (equivalent to 1905 levels) and the removal of the changed ocean–atmospheric mean state due to human influence over the last century from the initial conditions. The change state was estimated from a five-member ensemble of the HadGEM3 CMIP5 long run (2000–20 minus 1861–1950). The resultant ensemble mean forecast difference indicates about 3°C warming over southeast Australia due to atmospheric CO₂ increase and the associated ocean and atmospheric mean state change for this event (Fig. 1c). Further details are discussed in S. Abhik et al. (unpublished manuscript). Development is still underway to apply this method in the current operational version, ACCESS-S2. A detailed analysis of the circulation changes associated with the event can be drawn from the results of the SPA technique, as shown in Grose et al. (2018).

Fraction of attributable risk (FAR) method. A second, established approach that can be applied to understand the likelihood of surpassing certain thresholds for a particular variable (e.g., Victoria state-averaged month-long temperature) is to define the probabilities of exceedance in large ensembles of climate model simulations with full historical (or near future) forcing versus those with natural forcing (e.g., Lewis et al. 2014). The PDFs are being created again so that we have scope to update the thresholds used and move to include new CMIP simulations as they become available. Preliminary results suggest that the average January 2009 daily maximum temperature in Victoria, Australia, was 2.8 times more likely in the modeled present climate compared to a world with only natural forcing. The FAR technique could be applied
to extremes forecast in the S2S outlook period using appropriate bias correction to instantly provide an estimate of the contribution from anthropogenic climate change to the likelihood of that event under different climate conditions. An evaluation of the forecast skill would precede efforts using this approach, and discussion has begun with BoM Research to Operations staff working on verification and bias correction.

Statistical multivariate analysis of drivers. While climate change is one factor influencing extreme events over Australia, large-scale drivers such as El Niño–Southern Oscillation (ENSO) (e.g., Black and Karoly 2016; Karoly et al. 2016) and the Indian Ocean dipole (IOD) (e.g., Abram et al. 2021) lead to large climate anomalies in Australia. Thus, both scientists and Australian climate information stakeholders are keen to understand the interplay of these factors. For instance, the extreme rainfall across eastern Australia in September 2016 was linked to the negative phase of the IOD (King 2018), and if this information were provided in real time, decision-makers could anticipate a continuation of wet conditions through spring. If we have more accurate quantification of the impacts from influential large-scale climate drivers on the intensity or likelihood of regional climate extreme events and the influence of climate change on the drivers, then for future extreme events communities will be able to take appropriate adaptation measures, such as flood defenses.

To quantify the contribution from the large-scale drivers, we follow the approach of Wang et al. (2016), who describes a multiple linear regression (MLR) approach, with predictors chosen to represent the variability from ENSO, IOD, the southern annular mode (SAM), grid-ded antecedent soil moisture over Australia, and the mean global temperature, as used by Arblaster et al. (2014) and Hope et al. (2016). A deep understanding of the features that influence the climate of a region and season, and their interactions, is needed prior to setting up the system (e.g., Min et al. 2013); also, further development of the statistical approach might be considered to help provide causal reasoning based on the statistical relationships (e.g., Kretschmer et al. 2021). Once that understanding is established, the evaluation of the seasons and regions where large-scale modes of variability have high forecast skill for the event in question will guide the development of the MLR system to be applied to forecast extremes (e.g., Marshall et al. 2013, 2021; White et al. 2014).

The average January 2009 Victorian daily maximum temperature is reconstructed in Fig. 1e using the MLR approach. In this case, the majority of the anomalous heat can be explained by the linear trend, with small positive contributions from tropical and extratropical drivers. Slightly wet conditions in the months preceding January 2009 added a weak cooling effect to the reconstructed maximum temperature. Note that the current MLR holds little skill for January, explaining only ~25% of the average monthly daily maximum temperature, and further improvements in method and choice of predictors is underway.

Summary of attribution message using three methods, and next steps. For the 2009 heatwave event, preliminary results using three attribution methods indicate that the heatwave was made almost 3 times more likely and around 3°C hotter in the present climate than in a world without human influence on the climate. The usual drivers of heat in southeast Australia (ENSO and SAM) contributed only a small amount to the January temperature anomaly.

The SPA approach can capture the magnitude of the anomaly due to the background human influence on climate, while the MLR approach uses only a linear trend, which may be appropriate for heat extremes but may not work as well for rainfall. Likewise the circulation changes shown in the SPA experiments will capture the nuance of the forecast drivers of the event, which may differ from what might be captured with indices alone.

Improvements and developments might include moving the MLR or FAR approaches to submonthly values to better encompass the heatwave dates, or including further predictors.
such as the Madden–Julian oscillation in the MLR analysis e.g., (Marshall et al. 2021). More details about the drivers and circulation changes due to human influence could be gained from further examination of the S2S attribution experiment. Testing of the MLR and FAR for forecast events will also form part of the next steps.

Note that in all of these approaches, there is a reliance on the veracity of the forecasts, and the service will describe the forecast event, rather than an actual event. In the development of the system the hindcast skill will inform how much confidence can be given to the attribution assessments. For events with known low forecast skill, guidance would be given that more certain results will be provided shortly following the event using the two statistics-based methods (MLR and FAR), once indices and threshold can be based upon observations.

Other methods. Another approach to determining the influence from large-scale drivers and their interplay with long-term trends on an event again uses the BoM’s S2S prediction attribution system with modified initial conditions, such as the addition of the observed long-term trends on the canonical state of the ocean during El Niño (Lim et al. 2019) or La Niña (Lim et al. 2016). In each of those studies, the interactions with the underlying observed ocean trend were accounted for in the experimental design. These sorts of experiments could be predefined and triggered with the forecast of an extreme event; however, they are computationally expensive and thus are likely to form part of a post-event review rather than an integral part of the real-time service.

Another source of information could be drawn from methods being developed for other real-time attribution services in Europe and New Zealand.

The potential of the Extreme Event Explainer Service to boost existing services within the Bureau of Meteorology.

Decision support. Staff in this area of the BoM support the weather and climate information needs of users, such as fire agencies. As we described our plans for the real-time Event Explainer systems to these staff, they were quick to see the value for the post-event reviews that they produce following major fires. These reviews help highlight what worked well and what could be improved across the actions taken toward preparedness and response to the event. A part of this is an understanding of the drivers of the event, including the meteorological setup and the larger-scale modes of variability such as ENSO, the IOD, and the SAM and their interactions. The contribution of climate change is also important because it will add to the information around the conditions forecast for any upcoming fire season, allowing for informed risk assessments and longer-term planning that incorporates the changing likelihood and nature of extremes.

Seasonal prediction. The development of the Event Explainer service is closely linked to the operational seasonal forecast service. Understanding and quantifying the various causes of events in the outlook helps provide clarity and confidence in the messages provided. The tools used can also inform the model forecast skill verification and understanding; for example, the reasons that a seasonal forecast verifies poorly may be untangled if one looks to the relative contributions post priori (Lim et al. 2021).

Climate services for emergency management, hydrology, and agriculture. The BoM provides targeted services for key sectors across the community. For instance, forecasts are used to provide a heatwave service following learnings from the 2009 heatwave (Bettio et al. 2018). The service for hydrology presents historical risk, real-time forecasts and projections information all in one place: http://awo.bom.gov.au/. An additional statement around the drivers of extremes as

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they are forecast would complement those services and provide the link between what we are currently seeing and the projected changes in those same variables. Extending the Event Explainer service to include hydrological variables could form an important next step.

*Weather forecasters.* The real-time aspect of the system will help forecasters articulate informed answers to questions such as “How much did climate change influence this particular weather event?” that are often asked during media interviews about recent extremes. Furthermore, climate change can influence extreme weather events, pushing them outside the range of past experience. This information is thus important in communicating the current forecast risk, so actions are equal to the actual risk and not dependent on past behavior.

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Development of a Rapid Response Capability to Evaluate Causes of Extreme Temperature and Drought Events in the United States

Joseph J. Barsugli, David R. Easterling, Derek S. Arndt, David A. Coates, Thomas L. Delworth, Martin P. Hoerling, Nathaniel Johnson, Sarah B. Kapnick, Arun Kumar, Kenneth E. Kunkel, Carl J. Schreck, Russell S. Vose, and Tao Zhang

In January 2021 work began on a NOAA Climate Program Office funded project “that develops and tests a potential rapid event analysis and assessment capability” (NOAA Climate Program Office 2020). This 3.5-yr effort brings together scientists from four NOAA Laboratories/Centers and university scientists at two of NOAA’s Cooperative Institutes. This funded project has two high-level goals: 1) to address outstanding dataset, model, and methodological gaps in explaining extreme events within a changing climate, and 2) to build a prototype rapid event attribution system for temperature-related and drought extremes that could eventually serve routine climate information needs at local, state, and regional levels. The focus on temperature-related extremes derives from the conclusions of the U.S. National Academy of Sciences report that confidence in attribution findings is greatest for this class of extremes (National Academies of Sciences Engineering and Medicine 2016). The project will leverage additional research projects that were funded under the same call that focus on the underlying mechanisms for these types of extreme events.

Several climate trends in the United States present challenges for the attribution of temperature-related extremes (Fig. 1). The first is the lack of appreciable
daytime warming during the hottest time of year over the central United States—a so-called “warming hole” (Figs. 1a,b). This poses a conundrum in the attribution of heat waves in this region both scientifically and in perceived relevance and will require that the long-term trend itself be adequately explained. A second phenomenon is the increase in summertime soil moisture in the central United States concomitant with the upward observed trend in precipitation (Fig. 1c), contrary to trends predicted by many climate models (e.g., Dai 2013), posing an analogous challenge for drought attribution over the central United States. In contrast, there has been prevalent drought in the western United States since the turn of the millennium whose causes (Lehner et al. 2018; Seager and Hoerling 2014; Hoell et al. 2022), and implications for extreme event attribution, are yet to be definitively unraveled. While understanding these trends constitutes an important prelude to attribution of single events, the rest of this perspective concerns the development of an extreme event attribution capability within NOAA.

**Why a rapid assessment capability?**

The scientific value of extreme event attribution has been well described in the literature (e.g., Stott et al. 2013, 2016). While the science community often produces research explaining previous events [e.g., as part of an annual special issue of the Bulletin of the American Meteorological Society beginning with Peterson et al. (2012) and most recently Herring et al. (2021)], the methodology, datasets, and scientific focus of such studies are not uniform nor are they produced routinely and predictably. While this diversity of analytical approaches is a strength of the larger research enterprise, it poses some shortcomings as a potential climate service. This project seeks to address some of these shortcomings by providing a transparent and reproducible quantification of the changing weather and climate hazard along with the reasons for these changes, using a set of standard and well-documented methods and datasets. The aim is to create attribution information usable in the public and private sectors for planning analogous to the manner in which weather forecasts are produced, representing a new service for building climate resilience (Rogers and Tsirkunov 2013; Pulwarty and Sivakumar 2014). Additionally, the release of such data aims to improve climate information equity by making resource-intensive risk analysis (often the product of analyzing terabytes of data) publicly available after major events.

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**Fig. 1.** Climatic trends lead to challenges in attribution of temperature and drought. (left) Summer (JJA) daily maximum surface air temperature (°C) shows no positive trend over the central United States (black box) whereas (middle) daily minimum surface air temperature (°C) has warmed. (right) Precipitation (mm) has increased over this area consistent with increasing soil moisture. (top) Change maps are for the period 1920–2019, determined from endpoints of a linear regression fit. (bottom) The time series for the central U.S. region are for the 1895–2019 departures relative to a 1895–2019 mean. The 1920–2019 linear trend is shown by the superposed line.
How does this project define rapid? During and immediately following a high-impact extreme event there is considerable public interest in its likely causes, motivating the development of a capacity for quasi-real time analysis. There is also a longer time frame of interest. After an event there is a period of recovery, planning, and re-investment as the affected communities move toward rebuilding and seek to incorporate practices to increase resilience. The perceived risk of another such an extreme event often increases during this period (whether justified or not), and new perceptions affect subsequent planning for future disasters (Birkmann et al. 2010; Kousky 2010). During this planning stage in an events aftermath, a re-evaluation of the hazard posed by such events is important for determining resilience (Amaratunga and Haigh 2011; Pascale et al. 2020). The National Academy of Sciences report on event attribution noted that the science of the causes of these events can inform “emergency managers, regional planners, and policy makers at all levels of government” (National Academies of Sciences Engineering and Medicine 2016), although we recognize that the value of event attribution for informing adaptation is a matter of ongoing debate (e.g., Hulme et al. 2011).

For this project, “rapid” thus entails two time frames with different audiences: the first, as the event is ongoing and immediately following when public interest is high, and the second in the weeks to months following the event when accurate present-day and forward-looking risk assessments are desired by risk managers, policymakers, and affected communities. To reach the audiences for this information, this project will work with existing climate service providers and boundary organizations within and outside NOAA, including the NOAA Regional Climate Centers and Regional Integrated Sciences as Assessments (RISA) that have established communication channels and stakeholder networks.

Fig. 2. Key objectives of the rapid attribution prototype viewed as an iterative development process.
Key aspects of a rapid attribution prototype.

The project objectives are organized around five principal steps in conducting a timely extreme event attribution (Fig. 2), spanning the pre-event preparation of data and tools to the post-analysis communication of scientific findings. We see this as an iterative process, with lessons learned from event analysis feeding back into research and development. Key aspects are listed in the following subsections.

Pre-event research and development. An early project objective is the selection, development (as needed), and evaluation of a standard “core” collection of observational and model datasets for rapid attribution. The core observational datasets for analysis of heat and cold extremes comprise both station and gridded data; a dewpoint temperature dataset is under development in order to more meaningfully investigate heat stress extremes, particularly where temperature trends are weak. The core model simulations will consist primarily of large ensembles of free-running coupled model simulations [Coupled Model Intercomparison Project (CMIP)-style; e.g., Eyring et al. 2016] and boundary-forced atmosphere model simulations [Atmosphere Model Intercomparison Project (AMIP)-style; e.g., Gates et al. 1999], along with seasonal forecasts from initialized versions of these modeling systems. The use of large ensembles allows for better statistical sampling of rare extreme events, and such ensembles have become well established in the study of climate variability and change, as well as in attribution (e.g., Stone and Allen 2005; Kay et al. 2015; Sippel et al. 2015). To enlarge the compass of existing model simulations, team members are producing large ensembles using the GFDL-SPEAR (Delworth et al. 2020), NCEP FV3/GFS (Zhou et al. 2019), although at coarse resolution, and NCAR CESM/CAM5/6 modeling systems (Neale et al. 2010; Danabasoglu et al. 2020).

Model-based attribution frameworks will also be evaluated, including comparison of attribution from coupled models, long historical AMIP simulations, and time-slice simulations with modified boundary conditions ( “counterfactual” simulations in which known climate change drivers are withheld; e.g., Christidis et al. 2013, 2015; Seager and Hoerling 2014; Sun et al. 2018; Hoerling et al. 2019). Model and observational datasets, including capabilities to intercompare and diagnose these datasets, will be made available through this project, including through the Facility for Weather and Climate Assessments (FACTS; Murray et al. 2020).

Event monitoring and triggering protocols. The project will explore physically based, objective definitions of extreme events, aware of regional differences in what constitutes an event extreme. The distributions of historical extremes occupy a broad spectrum of intensity, duration, and extent, posing a challenge for monitoring. However, temperature extremes and droughts tend to be regional in scale, and/or have large-scale meteorological drivers associated with them, and these scales will guide our initial monitoring and analysis. Using objective criteria we will develop a library of past events for use in methodological development and evaluation, including the evaluation of potential new methods and tools. These criteria also open the door to using forecast guidance for anticipatory monitoring to enable more timely assessments as events unfold. Existing monitoring efforts and widely used indices will be evaluated for developing triggers for event assessment.

Initial observational analyses. An event, perhaps ongoing, will be promptly characterized relying primarily on core datasets. This quasi-real-time analysis of conditions on the ground serves several purposes: to hone in on a definition of the event that reflects its “extreme” physical characteristics, to place such events in the historical context of known variability and trends in frequency of occurrence, and to identify proximate drivers for further analysis. Issues of data homogeneity, completeness, and quality (Easterling et al. 2016), as well as data latency and potential missing or delayed observations during extremes, are among the challenges in
conducting a timely assessment. These difficulties notwithstanding, the objective is to provide timely and accurate characterization of the event, including placing the extreme event within an appropriate historical context, while withholding statements on causality until careful diagnosis is completed.

**Detailed causal analysis.** Following the characterization of the event by observational analysis a detailed causal analysis will be performed. The analysis will focus both on the change in probability of the event and on the likely contribution of various causal factors to the magnitude of the event, including both thermodynamic and dynamic drivers. The primary objectives of this analysis include determining the unconditional change in probability and magnitude due to anthropogenic forcing as well as the conditional change given various proximate drivers such as coincident SST and sea ice conditions [e.g., see the discussion of unconditional and conditional attribution in National Academies of Sciences Engineering and Medicine (2016)]. Other conditioning factors may also be considered, including atmospheric circulation anomalies and antecedent land surface conditions, as motivated by the observational analysis of the event.

The primary approach will be probabilistic analysis of the global large ensembles described above. Large ensembles allow for a reduction in errors in attribution due to sampling bias and allow for a better characterization of the role of internal variability. AMIP ensembles are included among the attribution methodologies for several reasons. First, AMIP simulations have a smaller climatological bias than the less constrained coupled simulations. Second, AMIP simulations can be viewed as an “empirically constrained” model that bridges the gap between purely observational analysis and coupled models. Third, they include the specific boundary forcing operating during an event. For these reasons AMIP simulations will be particularly useful in elucidating the causes of events where the observed regional trends are not well aligned with those expected from coupled models but are better simulated by the AMIP ensembles.

**Communication of event attribution.** At each stage above we will develop and evaluate possible communications messages, platforms, and partners. We will establish a protocol for clear-language statements of causality and changing risks, and the staging of publicly released information on extreme event assessments. Considerable synthesis will be needed to bring the different lines of evidence into a coherent set of attribution statements. To help inform planning and policy it will be essential to place the attribution findings in the context of climate projections. Conditional attribution—that is, attribution that takes into account particular conditioning factors such as the phase of El Niño, anomalous atmospheric circulation patterns, or other factors that are specific to environment in which the extreme event takes place—allows for “storyline” narratives to bolster credibility where unconditional attribution of global warming impacts is not sufficient (Shepherd 2014; Lloyd and Oreskes 2018)

As a research project within NOAA we will primarily leverage or adapt established capabilities of NOAA National Center for Environmental Information (NCEI) to disseminate results to the public, as NCEI routinely issues climate assessments and summaries in plain-language format [see NOAA NCEI (2021) (https://www.ncei.noaa.gov/news/national-climate-202106) for an example of a plain language climate assessment]. We will also issue our reports as research (experimental) products for others in our intended audience. As our intended audience spans the technical perspective of disciplinary reviewers and scientists and the broader perspective of decision-makers and the interested public, we recognize the need to communicate at multiple technical and conceptual levels.
Concluding remarks.
The Texas cold wave of February 2021—occurring only a month after project inception—allowed us to start exercising some of the proposed observational datasets and learn some preliminary lessons. The first lesson is the extent to which data latency may constrain the quality and timeliness of an initial observational analysis. A reasonably complete roster of preliminary gridded products and station observations with long period of record was available within 4 days from the peak of the event. However, it was apparent that several stations in the hardest-hit areas had missing or delayed reports, likely due to power outages. As in the analogy of a flood that wipes out stream gauges, the most extreme reports might be missing. The second lesson is the difficulty in characterizing the event as it was unfolding. While the severe impacts were focused in the southern Great Plains, the temperature extremes themselves spanned a much larger geographical region and emerged earlier (Fig. S1a in the online supplemental material). The best way to define this “extreme event” from a physical perspective, taking into account intensity, duration and extent, is not immediately clear. However, it was clear that regional indices (Fig. S1b) captured the severity of the event better than a nationwide index. Also, a notable negative skewness of the temperature distribution was recognized over the impact region—there have been 3-sigma cold events, but no 3-sigma warm events—alerting us that unconditional probabilities for an extreme cold wave are greater than had a Gaussian distribution been assumed (Fig. S1c; see also Tamarin-Brodsky et al. 2020; Loikith and Neelin 2019; Sardeshmukh et al. 2015). Because the project is only starting and the core datasets are still under development, these preliminary analyses were used only to guide the research component of the project and were not disseminated.

Recognizing that event attribution science is an emerging field, rapid attribution will of necessity be provisional. Different methodological choices can yield different results for the same event (e.g., van Oldenborgh et al. 2017). Therefore, we view the ability to re-attribute past events in order to systematically evaluate methods and datasets as essential to our research project.

The vision for this research project is to establish capabilities central to the development of a NOAA operational event attribution function that would regularly and reliably report on the likely causes of extreme events in the context of climate variability and change. The focus of this prototype development is on extremes in the United States and outlying territories (NOAA Climate Program Office 2020). International or interagency collaboration on the attribution of events worldwide can be facilitated through the use of this project’s global public datasets and proposed analysis tools. While we are just getting started, our goal is to build a transparent and open extreme event attribution system that serves NOAA’s mission to understand and predict changes in climate and weather and share that knowledge and information with others.

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AMERICAN METEOROLOGICAL SOCIETY


How to Provide Useful Attribution Statements: Lessons Learned from Operationalizing Event Attribution in Europe

Friederike E. L. Otto, Sarah Kew, Sjoukje Philip, Peter Stott, and Geert Jan Van Oldenborgh

Operational attribution protocols ensure transparency of assessments; communication needs to include future changes in extremes and meteorological development of the event to add value in local decision making.

In the immediate aftermath of an extreme weather- or climate-related event, the question is invariably asked whether and to what extent it was influenced by anthropogenic climate change. As a trusted source of weather information, national meteorological services (NMSs) in particular are facing this question and given their status as government services they are expected to answer, leading to calls for operationalizing event attribution studies. Under the umbrella of Copernicus, the European climate service provider, a team of scientists and several NMSs started a pilot project, following established protocols (van Oldenborgh et al. 2021; Philip et al. 2020) to test whether the task of attributing individual weather extremes can now be taken over by an operational service for the simpler extremes (e.g., cold and hot extremes or large-scale heavy rainfall).

While it has long been established that the likelihood and intensity of heatwaves and heavy rainfall events is increasing in a warming climate, the degree to which they are changing varies greatly depending on the exact temporal and geographical extent of the event (Harrington and Otto 2018; Leach et al. 2020).

In addition, anthropogenic climate change is far from being the only contributor to changing extreme

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weather events faced by natural and human systems. Other drivers such as population changes, water usage (Otto et al. 2015), surface roughness, or land use changes (Vautard et al. 2019) can also play a role. The final risk to extreme weather is compounded by exposure and vulnerability to hazards. These factors are continuously changing and in the short term the most amenable to protecting our society (e.g., through heat plans and updated building standards or improved water and drought management).

As such, it is important that all those aspects leading to damages and losses from extreme weather events that can be attributed and projected in a given location, like human-induced climate change, be disentangled from natural variability and other drivers in exposure and vulnerability in order to provide different European regions with the best available evidence to face global warming and give them ways to adapt to the changing nature of weather and climate extremes (van Oldenborgh et al. 2021; Shepherd 2019; Stone et al. 2021). To ensure relevance for society and decision makers it is extremely important to involve (local) exposure and vulnerability experts. Therefore, the pilot service decided not to use pre-calculated attribution statements (e.g., Christidis et al. 2015) but rather to follow the framework introduced by Philip et al. (2020), which takes these aspects explicitly into account.

When the pilot started, the science of attributing heatwaves and large-scale heavy rainfall events had been well established in the scientific literature with a large basis of scientific papers published, in particular on European events. For example the U.S. National Academy of Science assessed the “readiness” of these methods for implementation and concluded that for hot, cold, and wet events methods are indeed reliable (National Academies of Sciences, Engineering, and Medicine 2016). Thus, the primary aim of the pilot was not to test the reliability of the scientific methodology to attribute extreme weather events but to implement a scientific methodological approach into an operational protocol that can be applied within operational services and to test whether results are robust with respect to different models and datasets. These tests have been performed by undertaking four different event attribution studies, two slow ones reassessing previously published studies and two fast ones (see the online supplemental material) attributing previously unstudied events under quasi-real-time conditions.

In the remainder of this paper we discuss the two events that were re-attributed and compare them with the original attribution studies, we reflect on the functioning of the operational team, and finally we discuss several aspects that can act to strengthen attribution statements in the future. The term operational in this context means that clear procedures are followed that are independent of the event to be attributed and that the timeframe of the analysis is no longer than two weeks. We do not discuss whether event attribution should be operationalized but report on the outcome of the pilot project that was implemented following demand from national Met Services, who need to address questions on the role of climate change within the immediate aftermath of extreme events occurring.

Re-attributing of events.

The attribution procedure itself includes the trigger, the event definition, the trend detection in the observations, model evaluation, estimating the contribution from climate change, hazard synthesis, vulnerability and exposure analysis, and writing up the results. Based on an initial draft protocol, the attribution protocol has been tested thoroughly through test attribution studies each one led by a researcher from different NMSs. Two are highlighted below; the other two led to similar conclusions (see the supplemental material).

Figure 1 shows the direct comparison of the attribution results for the station of De Bilt. The main result of the study, the attribution statement that human-induced climate change has increased the likelihood of the event to occur by a factor of at least 1.8 (2020 analysis), is within the uncertainties of the rapid assessment from July 2018, which gave an increase in the likelihood of a factor of 3.3 (1.6 ... 16). The main reason for the differences is the slightly different event magnitude. For the 2020 analysis under Copernicus the summer of 2018 was over and thus the chosen event, the hottest 3-day maximum (TX3x), was estimated at a temperature of 33.7°C. The rapid study in 2018 was undertaken before the end of the summer, in July 2018, so TX3x, the hottest 3-day maximum of the year up until July, was only 33.0°C. The difference of 0.7°C in event magnitude has large consequences on the upper bound in the observations based probability ratio and changes it from 500 in the 2018 analysis to infinity. In consequence, a quantitative best-estimate of the role of climate change cannot be given in the 2020 analysis and the overall probability ratio is unbounded. This means that the uncertainty range is so large that only the lower bound can be meaningfully quantified. However, due to the fact that the models considerably underestimate the trend, the estimates of the lower bounds given in both cases are very conservative, potentially dramatically underestimating the role of climate change (Lloyd and Oreskes 2018).

Between 30 May and 2 June 2013 intense rainfall led to flooding in many parts of Germany, most significantly in upper areas of the Danube and Elbe Rivers. Although there were few casualties, the flooding caused millions of euros of damage. An attribution study of the event had been published (Schaller et al. 2014) finding no significant role of climate change. Revisiting the analysis of the rainfall in the 4-day period in late spring 2013, including six more observational years, we still found that despite expecting the intensity of rainfall to increase on
a global average as a result of climate change, there was no statistically significant increase in the likelihood of this event due to human-induced climate change.

In this second study, about half the models that were used and passed the evaluation showed a significant increase in the likelihood of the event to occur, leading to an overall increase in the model result, which overall leads to an inconclusive result for the Elbe but an increase for the Danube, although again not significant.

From a very high-level perspective the results of the 2013 and 2020 studies are thus the same. However, these estimates, if presented only as inconclusive and thus demonstrating no attributable change, would result in a very conservative estimate, potentially downplaying the role of climate change. We know this as in the slow study from May 2020 the same event was also assessed for a future warming level of \(2^\circ\), where for both basins an increase in the likelihood of a factor of 4.2 (Elbe) and 3.2 (Danube) respectively was found—a result that suggests that despite their statistical insignificance the trends toward a higher likelihood and intensity of the observed event are indeed due to climate change. This difference between models further supports the need for more process-based thinking to be included in future in operational attribution assessments in order to determine which models capture—or fail to capture—the relevant processes and thereby improve the robustness of such assessments, or indeed to lead to a change of the null hypothesis (Lloyd and Oreskes 2018). The third and fourth study are briefly described in the online supplemental material and highlight similar issues. Rapid attribution studies undertaken since by the World Weather Attribution Initiative (see the supplemental material) further corroborate the findings reported here.

Discussion.

Both events were performed by operational teams from the NMSs following a detailed protocol, and at the end of the four events the teams could do these attributions without guidance from scientists experienced in this established attribution framework. While a large team size ensures the use of multiple models and a wider public support, a larger team becomes more ponderous, with more decisions required and a higher level of detail in the protocol, yet still with need of expert judgment.

Both test studies showed that employing the published attribution methodology provides quantitative results that are robust against changes in models and datasets and, to the degree that this is expected in a non-stationary climate, also time. In that respect the protocols have been shown to be fit for the purpose and do not overplay the role of climate change (Bellprat and Doblas-Reyes 2016). However, the test studies have also shown that, especially when also taking the projected changes in the respective extreme events into account, the quantitative estimates are conservative.

It has been argued (Diffenbaugh 2020; Lloyd and Oreskes 2018; Lloyd and Shepherd 2020; Mann et al. 2017) that current practice is too conservative in emphasizing the robustness of the attribution assessment and focusing on lower bounds when these are least ill defined and thus underestimating the role of anthropogenic climate change and consequently misinforming the public.

These arguments are very valid, and follow-up research should investigate whether a storyline approach as suggested in Shepherd (2019) is more readily suited to operational attribution. Here we discuss, following social science research (Lahsen and Ribot 2021), whether the approach that has been used in the pilot delivers the local context of an event in a globally changing climate.

This purpose could be strengthened in the assessed pilot service by incorporating for example assessments of future changes in the likelihood of the event directly into the uncertainty assessment to calculate the synthesis result or to approach this issue within the communication of the results only and thus explicitly including prior information (Shepherd...
2021) and connecting to IPCC research. The former will however only be meaningful if the climate change signal has simply not emerged from the noise; if, however, drivers other than greenhouse gases (e.g., aerosols) mask the effects (van Oldenborgh et al. 2018), errors would be introduced. In any case systematically assessing the reasons for discrepancies between present and future changes will improve the usefulness of attribution studies.

Communications needs to be very clear on what the limitations of an individual event attribution study are (i.e., that they present a snapshot of the role of climate change on a very specific event at a point in time). This is also a strength, in that several key factors of that event are taken into account (e.g., circulation change, possible other drivers) that give a trend that deviates from the global mean one.

Having tested the developed protocols for operational attribution in two instances, the performance of the protocol and reliability of the results from a scientific point of view has been very successful. For the purpose of scientific appropriateness, the attribution protocol advocating the multi-model approach and improving on transparency is a currently available approach to event attribution that can be readily implemented in an operational process. Toward the future development of operationalizing event attribution, a conscious decision on where the service stands between risking overstating the role of climate change and underestimating it by issuing too conservative statements needs to be undertaken, taking new research on communication into account when possible. Furthermore a service needs to be clear on whether only the hazard or also vulnerability and exposure as well are included in the assessment. In the evolution of the service these decisions need to be taken into account when developing communication strategies.

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Record Low North American Monsoon Rainfall in 2020 Reignites Drought over the American Southwest

Andrew Hoell, Xiao-Wei Quan, Martin Hoerling, Rong Fu, Justin Mankin, Isla Simpson, Richard Seager, Cenlin He, Flavio Lehner, Joel Lisonbee, Ben Livneh, Amanda Sheffield

Model experiments suggest climate change increased the risk for record low American Southwest precipitation in June–September 2020, but confidence is low due to model biases and no significant observed trends.

Drought has plagued the American Southwest since 2000, leading to the second lowest estimated 19-yr average soil moisture in approximately 1200 years (Williams et al. 2020), fueling destructive wildfires (Fu et al. 2021) and inducing low flows in major rivers (Udall and Overpeck 2017; Hoerling et al. 2019). In 2020/21, drought deepened against the backdrop of two decades of accumulated drought damages that exceed $131.4 billion (NCEI 2021) and caused alarm about potential water delivery shortages in the Colorado River basin (U.S. Bureau of Reclamation 2021). The proximate causes for persistent regional droughts include low precipitation (Lehner et al. 2018) and increased evaporative demand in concert with warming temperatures (Crockett and Westerling 2018; Williams et al. 2020). While there is strong evidence for anthropogenic forcing of the warming trend (e.g., USGCRP 2018), recent work has also pointed to a potential human effect on Southwest precipitation (Pascale et al. 2017; Hoerling et al. 2019; He et al. 2020).

Precipitation deficits during the 2020 monsoon season were especially severe over Arizona, New Mexico, Colorado, and Utah (the Four Corners states) and were crucial in re-establishing the regional drought

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On 26 May 2020, the United States Drought Monitor (USDM; Svoboda et al. 2002) indicated that less than half of the Four Corners states area was in at least moderate drought (Fig. 1a). By 6 October 2020, 75% of the area was covered by extreme drought (Fig. 1b). June–September precipitation averaged over the Four Corners states was the lowest since at least 1895 (Figs. 1c,d).

Here we examine whether anthropogenic climate change influenced an unprecedented failure of 2020 summer monsoon rains that reignited drought conditions. We focus on the Four Corners states during June–September 2020 using observed analyses, historical coupled climate models, atmospheric models, and event-attribution experiments.

Tools and methods.

**Observed analyses.** Drought assessments are from the USDM (Svoboda et al. 2002).1 Observed precipitation analyses for June–September 1895–2020 are based on United States climate divisions (Vose et al. 2014).2 Precipitation for the Four Corners states is an area-weighted average for all climate divisions in Utah, Arizona, Colorado, and New Mexico.

**Model simulations.** Coupled climate simulations for 1920–2019 are diagnosed. One is the 40-member Community Earth System Model version 1 large ensemble (CESM1; Kay et al. 2015) and the second is the 30-member Seamless System for Prediction and Earth System Research (SPEAR; Delworth et al. 2020). A 10-member ensemble of Community Atmosphere Model version 6 simulations (CAM6; Danabasoglu et al. 2020) are also diagnosed. In all three, time-evolving
greenhouse gases and anthropogenic aerosols are specified: CESM1 following a CMIP5 protocol (Taylor et al. 2012) and SPEAR and CAM6 following a CMIP6 protocol (Eyring et al. 2016). CAM6 is further constrained by specified monthly observed sea surface temperature (SST; Huang et al. 2017) and sea ice variations (Rayner et al. 2003), and are employed since surface boundary conditions have been shown to play a role in shaping American Southwest precipitation (Schubert et al. 2016).

Event-attribution experiments are diagnosed using parallel 50-member ECHAM5 (Roeckner et al. 2006) atmospheric model ensembles for 1979–2020. The first ensemble (factual) is conducted like the CAM6 simulations in which the observed SSTs, sea ice, and chemical composition are specified based on monthly historical analyses. The second ensemble (counterfactual) sets the atmospheric chemical composition to circa 1900 values and removes observed 1900–2019 linear SST trends from their interannual variations [see Sun et al. (2018) and Hoerling et al. (2019) for details]. Two assumptions on long-term SST change are made: one in which observed zonally averaged SST trends are removed (cfv1) and the second in which the observed two-dimensional SST trend pattern is removed from time-evolving SSTs (cfv2). Simulated Four Corners states precipitation is obtained by calculating the average of all grid points in that four-state region. Model data may be obtained from the Facility for Weather and Climate Assessments (Murray et al. 2020).

Methods. Past (1920–79) and recent (1990–2019) climates are compared to estimate the effects of historical change in June–September precipitation. Such a comparison in the historical simulations isolates the effect of the prescribed forcing, which is mostly anthropogenic (Bindoff et al. 2013). For event-attribution experiments, the recent climate is given by factual ensembles for 1990–2019 and the past climate is given by the cfv1 and cfv2 ensembles.

Our principal metric for assessing climate change effects is the relative risk ratio (e.g., Otto et al. 2018) of low precipitation, where values larger than one indicate more frequent low precipitation in the recent climate relative to the past. Histograms are evaluated to calculate relative risk of change in seasonal precipitation falling below the 50% (median), 10% (decile), 5% (ventile), and 1% (percentile) thresholds of June–September precipitation. Confidence intervals of relative risk ratios are derived using a bootstrapping approach, given negligible temporal autocorrelation of June–September precipitation in the observed analysis ($r = −0.02$) and in the models (not shown). The bootstrapping approach is described in the online supplemental material.

Two approaches, both based on bootstrapping, provide a brief appraisal of model performance. The first compares the first three moments (mean, variance, skewness) of precipitation in the model’s past and recent climates to the observed analysis. The second compares the mean precipitation difference between past and recent climates in the models to the observed analysis. The bootstrapping approach is described in the supplement. In terms of regional precipitation characteristics, the mean, variance, and skewness of the models differ from each other and the observed analysis to varying degrees (Table 1). Some models simulate more realistic mean precipitation (e.g., SPEAR) while others simulate more realistic variability (e.g., ECHAM5), although no models simulate both well. In terms of average precipitation difference from past to recent climates, some models are able to simulate the small observed precipitation increase as a possible outcome within a 95% confidence interval of its bootstrapped simulated distribution (e.g., SPEAR, CESM1, ECHAM5 cfv1 in Fig. S1).

Results.

Whereas record low precipitation in June–September 2020 over the Four Corners states capped off a 3-yr stretch of below average rainfall (Fig. 1d), no significant trend since 1895 is
found (Figs. 1d and 2a; see also Fig. S1a in the online supplemental material). Further, no statistically significant change in the frequency of low precipitation is noted from past to recent climates (Fig. 2g). Given the brevity of observations, we use multiple models and large ensembles, controlled in various ways for historical climate drivers, to test the effect of climate change on low precipitation occurrences.

Four of five models indicate statistically significant decreases in mean June–September precipitation from past to recent climates over the Four Corners states, with only CESM1 dissenting (Figs. 2b–f). SPEAR and CAM6 simulate 0.089 mm day$^{-1}$ (7%) and 0.235 mm day$^{-1}$ (15%) mean precipitation declines, respectively, via a dry shift in the probability distribution from past to recent climates. The same climate change sensitivity in these transient experiments is also found in the ECHAM5 event-attribution experiments. All these experiments are consistent in their widespread precipitation decreases from past to recent climates over the American Southwest, though their spatial patterns differ (Fig. S2). The CESM1, in contrast, simulates a slight increase in June–September precipitation from past to recent climates.

Statistically significant increases in the risk of extreme low seasonal precipitation in the recent climate relative to the past is found across four of five models, given that the 95% confidence intervals exceed a relative risk of unity (whiskers in Fig. 2g). As indicated by changes in risk (dots in Fig. 2g), low decile occurrences for seasonal rainfall are found to be 1.5–2.5 times more likely, while the more extreme low percentile occurrences are found to be 2.5–5.5 times more likely in SPEAR, CAM6, ECHAM5 cfv2, and ECHAM5 cfv1. The 95% confidence interval, or uncertainty, is larger for smaller ensembles (cf. CAM6 and SPEAR) and precipitation thresholds that occur less frequently.

### Table 1. Mean, variance, and skewness of past (1920–79) and recent (1990–2019) climate precipitation in the observed analysis and bootstrapped model ensembles. Three values are provided for the model ensembles, the 2.5th (blue) and 97.5th (orange) percentiles to estimate the 95% confidence interval, and the median (gray).

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Variance</th>
<th>Skewness</th>
<th>Mean</th>
<th>Variance</th>
<th>Skewness</th>
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<tr>
<td>Observed analysis</td>
<td>1.256</td>
<td>0.057</td>
<td>0.374</td>
<td>1.281</td>
<td>0.058</td>
<td>0.459</td>
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<td>−0.431</td>
<td>1.851</td>
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<td>1.924</td>
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<td>1.959</td>
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<tr>
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<td>2.000</td>
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<td>0.943</td>
<td>2.067</td>
<td>0.138</td>
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<tr>
<td>SPEAR</td>
<td>1.132</td>
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<tr>
<td></td>
<td>1.212</td>
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<td>1.120</td>
<td>0.092</td>
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<tr>
<td></td>
<td>1.295</td>
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<td>0.947</td>
<td>1.236</td>
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<td>CAM6</td>
<td>1.464</td>
<td>0.078</td>
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<td>1.233</td>
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<tr>
<td></td>
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<td>0.051</td>
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<tr>
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<td>1.641</td>
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<td>0.974</td>
<td>1.491</td>
<td>0.084</td>
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<tr>
<td>ECHAM5 cfv1</td>
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<td>0.049</td>
<td>−0.220</td>
<td>0.665</td>
<td>0.041</td>
<td>−0.378</td>
</tr>
<tr>
<td></td>
<td>0.870</td>
<td>0.073</td>
<td>0.351</td>
<td>0.764</td>
<td>0.073</td>
<td>0.295</td>
</tr>
<tr>
<td></td>
<td>0.940</td>
<td>0.104</td>
<td>0.999</td>
<td>0.863</td>
<td>0.116</td>
<td>1.065</td>
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<tr>
<td>ECHAM5 cfv2</td>
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<td>−0.121</td>
<td>0.666</td>
<td>0.042</td>
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<tr>
<td></td>
<td>0.851</td>
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<td>0.763</td>
<td>0.073</td>
<td>0.293</td>
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<td></td>
<td>0.921</td>
<td>0.099</td>
<td>0.951</td>
<td>0.685</td>
<td>0.115</td>
<td>1.053</td>
</tr>
</tbody>
</table>
The decrease in precipitation from past to recent climates is consistent with the studies of He et al. (2020), which employed CMIP5 and CMIP6 models, and of Pascale et al. (2017), which employed a single model. Both studies point to an increase in atmospheric stability as a cause of precipitation decreases related to the North American monsoon, a result worth probing in future physically based attribution studies of June–September precipitation over the Four Corners states. Future physically based attribution studies would be strengthened by the use of models with higher horizontal resolution and models that permit convection. Models with higher horizontal resolution (e.g., 50 km) allow for a more accurate simulation of moisture surge events from the Gulf of California (Pascale et al. 2016) and convection-permitting models integrated at 2.5 km provide a reasonable representation of organized convection important to precipitation over the American Southwest during the monsoon season.

Discussion and concluding remarks.

Most model experiments used herein indicate record low June–September 2020 precipitation in the Four Corners states (Fig. 1) was made more likely due to climate change (Fig. 2), although our confidence in this result is low because such a change has not been observed since 1895 and the models do not perfectly reproduce precipitation statistics in the region.
(Table 1). Four of the five models indicate that low decile and percentile occurrences are 1.5–2.5 and 2.5–5.5 times more likely, respectively, due to climate change. The model results are consistent across three widely used experiment types—historical simulations using coupled and atmospheric models, and event-attribution simulations—which together provide a more robust test of anthropogenic effects than observations alone. Use of these large ensemble experiments allowed evaluations of extreme event probabilities to be directly calculated, which is a strength of the study, even though the models are not perfect representations of the Earth system. Our results are consistent with the regional precipitation decrease in a changing climate reported by Luong et al. (2017), which employed higher-resolution models that permit convection, although it should be noted that their study found precipitation decreases to be most prominent over Arizona.

An observed downward trend in June–September precipitation over the Four Corners states has not been observed as of 2020. However, the absence of such a trend is not sufficient evidence against an effect of anthropogenically forced drying. We note that some of the models can reproduce the small observed mean precipitation increase from past to recent climates (Fig. S1). Suggested hereby is that the absence of a drying trend over the last century could have resulted from internal variability masking a climate change drying.

One of five models indicate that climate change leads to a slight wetting of the region during June–September. This contrary indication of North American monsoon precipitation in a changing climate is consistent with Cook and Seager (2013), who found no significant change in total monsoon precipitation over Mexico and southern Arizona and New Mexico in CMIP5 models. However, He et al. (2020) found a significant drying of the core monsoon region over Mexico and Central America using CMIP5 and CMIP6 models, as did Moon and Ha (2020), Chen et al. (2020), and Cook et al. (2020) for projections of the end of the twenty-first century in CMIP6 ensembles. Cook et al. (2020) further points out that results from CMIP5 and CMIP6 are generally consistent, which suggests that the same sources of uncertainty remain the latest generation of climate models. The current study adds to these by focusing on the Four Corners region to the north, and future work would be wise to examine summer rainfall change across southwest North America. Such work would benefit, as here, from the use of large ensembles from which tail risks could be meaningfully evaluated.

Acknowledgments. The authors thank the editor and two anonymous reviewers for thoughtful and constructive comments that led to an improved manuscript. The authors also thank Mr. David Allured for conducting the ECHAM5 simulations and Dr. Judith Perlwitz for comments on an early version of this paper. The authors are grateful for the support of the NOAA MAPP Program and its Drought Task Force.
References


Anthropogenic Climate Change and the Record-High Temperature of May 2020 in Western Europe

Nikolaos Christidis and Peter A. Stott

The extremely warm May of 2020 in western Europe was favored by persistent high pressure, but human influence is also estimated to have made such events 40 times more likely.

Extremely warm temperature anomalies over western Europe in May 2020 (Fig. 1a) were characterized by summer-like extremes, with several French cities recording temperatures above 30°C for the first time in May, while in Spain temperatures locally exceeded 35°C. The event was linked to an omega blocking ridge pattern associated with significant warm advection over the region. Anomalies of the 500-hPa geopotential height (Z_{500}) from the NCEP–NCAR reanalysis (Kalnay et al. 1996) illustrate the prevalent anticyclonic conditions over western Europe in May 2020 (Fig. 1b). The anticyclonic pattern was embedded in a Rossby wave train extending over the whole Northern Hemisphere (see the online supplemental material), which was also linked to the severe heatwave in Siberia (Ciavarella et al. 2021). Interestingly, the month of May also had record warmth on a global scale (Di Liberto 2020). Here we present an attribution study that assesses how anthropogenic forcings may have changed the likelihood of extreme May temperatures in western Europe (10°E–5°W, 35°–55°N), both in the general case (i.e., under any possible synoptic conditions; unconditional analysis) and under the influence of a persistent anticyclonic circulation pattern (conditional analysis).
We use the HadCRUT4 observational surface temperature dataset (Morice et al. 2012) to compute regional mean May temperature anomalies. As in other attribution studies (Bindoff et al. 2013), we define anomalies relative to a period earlier than the common 1961–90 (here we use years 1901–30 as a baseline), since the earlier baseline is closer to the pre-industrial climate and thus allows us to capture most of the anthropogenic effect. HadCRUT4 time series since 1900 are illustrated in Fig. 1c and demonstrate that May 2020 is the warmest May in the record. We also construct distributions of monthly actual temperatures over a recent period with NCEP–NCAR reanalysis data for May and June (Fig. 1d). The distributions reveal that the May 2020 temperature is extreme for the month of May, but typical for June, which could manifest a change in seasonality in a warming climate (Christidis et al. 2007; Ruosteenoja et al. 2015).

We next compute temperature anomalies with data from 11 models (see the supplemental material) that contributed to the phase 6 of the Coupled Model Intercomparison Project (CMIP6; Eyring et al. 2016). We select models that provide ensembles of simulations with all historical forcings (ALL) and natural forcings only (NAT) that enable us to compare the likelihood of extremes in the real world and in a hypothetical natural world without the effect of human activity, following the popular risk-based attribution framework (Stott et al. 2016). The ALL simulations were extended to 2100 with the “middle-of-the-road” emissions scenario SSP2–4.5 (Riahi et al. 2017). We use in total 56 ALL and 62 NAT simulations. We apply standard evaluation tests for multimodel ensembles (Christidis et al. 2021; also see the supplemental material), which show that the modeled historical trends of the regional May mean temperature are consistent with HadCRUT4, but the modeled variability is somewhat larger. We therefore bias-correct the modeled data following the approach of Christidis and Stott (2021), whereby we remove the smoothed ensemble mean from the individual ALL time series, adjust their variability, and reintroduce the ensemble mean. After bias correction the modeled variability and temperature distribution agree well with HadCRUT4 (supplemental material). We highlight the bias correction as a caveat in our analysis, which may adversely affect future likelihood estimates, if future changes in variability are incorrectly represented by the models. Nevertheless, neither the observations nor the models suggest major changes in

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Fig. 1. Spatial patterns of the (a) temperature anomalies and (b) Z500 anomalies relative to 1961–90 for the month of May 2020 constructed with HadCRUT4 and NCEP–NCAR reanalysis data respectively. The yellow box marks the western European region considered in this study, selected as a European area that includes the warmest observed anomalies. (c) Time series of the May mean anomalies relative to 1901–30 averaged over the western European region. Time series were produced with HadCRUT4 data (black) and CMIP6 simulations with (red) and without (blue) human influence. The smoothed mean of the ALL simulations is marked by the thick white line. (d) Normal distributions of the 1961–90 actual mean temperature in western Europe for the months of May (black) and June (red) constructed with NCEP–NCAR reanalysis data. The colored areas lie between the 5th and 9th percentiles. The vertical blue line marks the May 2020 temperature.
in variability with time. Time series of the model simulations are depicted in Fig. 1c. Unlike the largely stationary NAT climate, the ALL experiment shows a steady temperature increase since the late twentieth century, leading to a warming of over 2°C by 2100 under SSP2–4.5.

**Unconditional attribution.**

We first compare the present-day likelihood of exceeding the 2020 observed anomaly (2.3°C) irrespective of the atmospheric circulation with what it might have been in the NAT climate. We construct the ALL distribution of May mean temperature anomalies using simulated data in years 2015–25 (56 simulations × 11 years). As the natural climate is stationary in the long run, we utilize simulated NAT anomalies of all available years. We find a major shift of the distribution toward warmer temperatures (Fig. 2a), leading to an estimated increase in the likelihood of the 2020 event of about 40-fold (Fig. 2b, Table 1). Its return time (inverse probability) is estimated to decrease from several centuries in the NAT world to about a decade in the present climate (Table 1), while by 2100 such an event could occur almost every year (estimate based on ALL data in years 2090–2100). As in previous work, extreme probabilities are calculated with the generalized Pareto distribution and associated uncertainties with a simple Monte Carlo bootstrap procedure (Christidis et al. 2013).

The available CMIP6 models contributed unequal number of simulations to our analysis, which introduces an uncertainty to our results. For example, the large number of CanESM5 simulations gives more weight to a model with a high climate sensitivity. We assess the associated uncertainty by removing the CanESM4 simulations from the ALL and NAT ensembles and repeating the analysis. We find that the ALL return time (best estimate) increases from 8.9 to

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**Fig. 2.** (a) Normalized distributions of the May mean temperature anomaly with (pink) and without (blue) human influence from the unconditional analysis. The vertical black line marks the May 2020 anomaly. (b) Risk ratio showing the increase in probability due to human influence. The vertical orange line marks the best estimate (50th percentile). (c),(d) As in (a),(b), but for the conditional analysis with probabilities estimated for months with a similar circulation to May 2020. (e) Normalized distributions of the May mean temperature in the present-day climate for seasons with high (pink) and low (gray) correlations to the May 2020 circulation pattern. (f) Risk ratio showing the increase in probability due to the atmospheric circulation effect.
Table 1. Attribution results. Best estimates of the return time, the risk ratio, and their associated 5%–95% uncertainty range (in brackets). Results shown for the unconditional analysis, the analysis conditioned on the circulation pattern and for the assessment of the circulation effect. Return times are shown with (ALL) and without (NAT) the effect of human influence. Conditional estimates use modeled months with high (>0.6) and low (<0.6) correlations with the 2020 circulation pattern.

<table>
<thead>
<tr>
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<th>Return time (yr)</th>
<th>Return time (yr)</th>
<th>Risk ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unconditional attr.</td>
<td>ALL</td>
<td>NAT</td>
<td>Pr(ALL)/Pr(NAT)</td>
</tr>
<tr>
<td>(General case)</td>
<td>8.90 (7.65–10.78)</td>
<td>367 (281–527)</td>
<td>41.27 (29.47–60.36)</td>
</tr>
<tr>
<td>Conditional analysis</td>
<td>ALL-high</td>
<td>NAT-high</td>
<td>Pr(ALL-h)/Pr(NAT-h)</td>
</tr>
<tr>
<td>(2020-like circulation)</td>
<td>4.15 (3.45–5.29)</td>
<td>119 (35.23–180)</td>
<td>28.37 (8.72–44.42)</td>
</tr>
<tr>
<td>Circulation effect</td>
<td>ALL-high</td>
<td>ALL-low</td>
<td>Pr(ALL-h)/Pr(ALL-low)</td>
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<tr>
<td></td>
<td>4.15 (3.45–5.29)</td>
<td>12.94 (10.43–16.57)</td>
<td>3.10 (2.29–4.28)</td>
</tr>
</tbody>
</table>

about 15 years, while the NAT probability is less affected and changes from 367 to 393. The risk ratio is thus reduced from 41 to 26. Despite these differences, we conclude there is a broadly consistent indication of the estimated anthropogenic impact in terms of its order of magnitude but acknowledge the uncertainty in our results linked to the ensemble construction.

We also conduct an independent assessment with HadCRUT4 observations using the approach of Christidis and Stott (2021). We first remove the smoothed forced change from the observational time series, based on the ALL ensemble mean (white line in Fig. 1c). The remaining anomalies in years 1900–2020 provide the NAT probability. We then add back the forced response corresponding to year 2020, estimated again from the ALL ensemble mean, and compute the ALL probability. The ALL probabilities from HadCRUT4 are in good agreement with CMIP6 (return time: 9 years, uncertainty range: 6–15 years). The smaller NAT probabilities have large uncertainties as they cannot be adequately estimated with the smaller observational sample. Nevertheless, the lower bound of the NAT return time is also of the order of a few hundred years, similar to what the models suggest.

**Conditional attribution.**

We next derive ALL and NAT probabilities for the extreme event under anticyclonic conditions similar to those in May 2020. As in previous work (Christidis et al. 2018), we sub-sample the model anomalies by selecting months that have similar or different circulation patterns to May 2020 over the reference region, as determined by correlation coefficients above or below 0.6. We confirm that estimating correlations over wider areas would not considerably change our attribution results. Pattern correlations between the reanalysis Z500 anomalies in May over western Europe (Fig. 1b) and simulated May anomalies are thus computed. We then use the high-correlation samples (ALL-high and NAT-high) to infer conditional probabilities (Table 1). We find again that human influence clearly shifts the distribution to warmer temperatures (Fig. 2b), making the 2020 event about 30 times more likely to occur (Fig. 2c, Table 1). As expected, the return times of warm extremes are lower in the conditional case compared to the general case, since the presence of anticyclonic conditions favors warm anomalies. However, the estimated risk ratio is of the same order as in the general case. We finally assess how much more likely the event becomes in the present-day climate under persistent anticyclonic conditions compared to other circulation states. We do this by comparing the ALL-high and ALL-low probabilities (Figs. 2d,e, Table 1) and estimate that May months at least as warm as 2020 become 2–4 times more likely.
Discussion.
Using a suite of 11 state-of-the-art climate models we show that the unprecedented May temperature of 2020 in western Europe is becoming increasingly common under the influence of anthropogenic forcings. There are of course uncertainties in model-based assessments (e.g., biases, model limitations, future emission scenarios), but the level of agreement with simpler approximate probability estimates from observations is reassuring. The models suggest that the return time of May heatwaves with temperatures at least as high as in 2020 has been reduced from centuries to under a decade, although the precise estimated change is sensitive to the ensemble used, as already discussed. While spring heatwaves may generally be expected to have less adverse impacts than summer heatwaves, continuous warming in western Europe means that May would gradually bear a closer resemblance to summer months with possibly serious socio-economic repercussions (e.g., increased heat stress and mortality spikes, strain on energy and water availability, increased wildfire risk, agricultural losses, etc.). Therefore, attribution studies like ours provide valuable information to help communities reduce their vulnerability to anthropogenic climate change.

Acknowledgments. This work was supported by the Met Office Hadley Centre Climate Programme funded by BEIS and Defra.

References


Anthropogenic Contribution to the Record-Breaking Warm and Wet Winter 2019/20 over Northwest Russia

Jonghun Kam, Seung-Ki Min, Yeon-Hee Kim, Byeong-Hee Kim, and Jong-Seong Kug

CMIP6 simulations suggest that the 2019/20 extremely warm and wet winter over northwest Russia would have been extremely unlikely without human influence despite a strong positive phase of the NAO.

Northwest (NW) Russia has been experiencing increased snow-free days since 1966 (Bulygina et al. 2011), and the 2019/20 winter was warmest on record since 1902. It resulted in a significant shrinkage of snow cover and thus required the delivery of artificial snow from dispatching trucks for the New Year celebrations (Ilyushina and Miller 2020). The 2019/20 winter was also wettest on record since 1902, in line with the northern high-latitude moistening trend under greenhouse warming (Min et al. 2008; Wan et al. 2015). The NW Russian winter climate plays an important role in shaping the Eurasian spring/summer climate through its delayed impacts. Typically, the regional warm winter during the positive phase of North Atlantic Oscillation (NAO) or Arctic Oscillation can cause premature snowmelt and drier soil, providing a favorable condition for severe heatwaves and wildfires (Bamzai 2003; Kim et al. 2020). However, understanding of anthropogenic contribution to the 2019/20-like extremely warm and wet winter over NW Russia remains to be determined.
Here, we investigate the anthropogenic impact on the likelihood of the 2019/20-like warm and wet winter over NW Russia by quantifying the contributions of anthropogenic (greenhouse gas and aerosol) forcing, natural (solar + volcanic) forcing, and internal variability (focusing on the NAO) to the 2019/20 NW Russia winter. The findings of this study alert policy makers and local stakeholders of the expected change in the risk of climate change–driven extremes.

**Data and methods.**

First, we computed the geopotential height anomalies at 850 hPa and vertically integrated moisture flux anomalies relative to the 1981–2010 climatology from the latest version of the European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis (ERA5)\(^1\) for analysis of NAO influences (Fig. 1a). We calculated regional averages of wintertime [December through February of the following year (DJF)] 2-m air temperature (T2m) and precipitation (PREC) over NW Russia (30°–52°E, 58°–68°N) from Climate Research Unit (CRU) version TS v4.04 (Harris et al. 2020) and 42 station observations from the Russian Research Institute of Hydrometeorological Information, Water Data Center (RIHMI-WDC)\(^2\) (Figs. 1b,c). Then, we computed the anomalies of T2m and PREC relative to the 1902–31 climatology to analyze global warming influences. Based on the temporal correlation maps, we found that this region is highly correlated with the regional climate of the western part of Russia (up to 70°E and 50°N; not shown).

Here, we used 76, 65, 74, and 68 ensemble members of 12 models from the phase 6 of the Coupled Model Intercomparison Project (CMIP6) with historical (H), greenhouse-gas (G), historical-natural only (N), and aerosol (A) forcing, respectively (Eyring et al. 2016). First, we selected these ensemble runs of the 13 models based on the availability of multiple ensemble members (≥ three ensemble members for H-, G-, N-, and A-forcing, except for BCC and CAS), and then we selected the ensemble runs of the 12 models based on the performance in the seasonality of simulated T2m and PREC anomalies (see Figs. S1 and S2 in the online supplemental material). The runs with H-forcing (ending in 2014) were extended up to 2020 using the corresponding Shared Socioeconomic Pathway (SSP) 2-4.5 scenario runs, which were chosen based on the data availability considering their similar radiative forcing over 2015–20 (O’Neill et al. 2016). We chose the SSP 2-4.5 scenarios runs for H-forcing for consistency with other forcing runs (Gillett et al. 2016). Details of the ensemble members for each model are provided in Table S1.

We used a bilinear method to interpolate all model data onto the observed grids (50 km × 50 km) and then computed the regional averages over NW Russia (Figs. 1d,e). Next, we estimated the contributions of H-, N-, G-, and A-forcing to the observed anomalies of T2m and PREC during the 2019/20 winter (Figs. 1f,g). Here we estimated individual forcing contributions to the observed anomalies, using the 10-yr (2011–20) averages of their multimodel multi-ensemble means (MMMs) of T2m and PREC anomalies, following Knutson et al. (2013) and Knutson and Zeng (2018), who compared multimodel mean forced anomalies with observations. To construct the 95% confidence interval (CI) of each forcing’s contribution, we resampled the 10-yr (2011–20) segments 76 times [e.g., the total sample size for H-forcing is 760 (10-yr segment × 76 ensemble runs)] by weighing each model based on the model’s contribution to the total ensemble runs [e.g., 10/76 for CNRM-CM6-1, which has 10 members], and repeated resampling with replacement 1,000 times.

It is well known that the NAO shows the decadal-consistent impact on the western part of Europe winter climate, including NW Russia (Marshall 2021). It showed a very strong positive phase (NAO+) during 2019/20 winter (Juzbašić et al. 2021), ranking 7th highest (NAO index = +1.26; see below) since 1951 (the 2014/15 winter had a record high value of +1.66). To mea-

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1. [https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5](https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5)
Fig. 1. (a) Geopotential anomalies at 850 hPa and vertically integrated moisture flux (black vectors) anomalies during the 2019/20 winter relative to the 1981–2010 climatology. (b) 2-m air temperature and (c) precipitation anomalies over the study region in the percentage relative to the 1902–31 climatology. In (b), circles depict the location of the 42 meteorological stations from RIHMI-WDC. Time series of (d) 2-m air temperature and (e) precipitation anomalies from the observational data (CRU: black solid lines and 42 stations: white dashed lines), and the CMIP6 simulation with H- (orange), G- (red), N- (blue), and A-forcing (green). In (d) and (e), the min-max ranges of the CMIP6 simulations with each forcing are shown at the center of the grand means. Also shown are the contributions of H- (orange), G- (red), N- (blue), A-forcing (green), and residual (gray) for the 2019/20 (f) T2m and (g) Prec. In (f) and (g), the error bars depict the 95% CIs from the 1,000 bootstrapping samples from the corresponding forcing runs and numbers in parentheses are the percentage contribution of each forcing/NAO to the observed 2019/20 anomaly value.
sure the NAO contribution to the observed NW Russian winter climate in 2019/20, we regressed the observed T2m and PREC anomalies onto the NAO index1 over 1951/52–2018/19, excluding the 2019/20 winter. Then, we computed the NAO contribution by multiplying the NAO index in 2019/20 with the linear regression coefficient and also constructed its 95% CI based on the 2.5th and 97.5th percentiles of the linear regression coefficients. The CMIP6 model-based analysis of NAO shows that the frequencies of high NAO index values from H-forcing and N-forcing runs are similar to each other, indicating that NAO is an internal mode (see Fig. S3).

To better understand whether the anthropogenic impact has been consistent at the decadal scale, we estimated the probability of occurrence of T2m or PREC anomalies (relative to 1902–31 means) exceeding the observed 2019/20 values through order statistics (i.e., counting the number of threshold exceedances) from the selected CMIP6 models with H-, N-, G-, and A-forcing from the 10-yr segments over 1986–95 (hereafter simply the 1990s) and 2011–20 (2010s). We selected these decades because the NAO index shows two positive phases over 1986–95 and 2011–20 from the observational data and CMIP6 simulations (see Fig. S3). Then we calculated the probability ratio (PR) for $P_{m}/P_{M}$, $P_{d}/P_{D}$, and $P_{d}/P_{N}$ for 1990s and 2010s. The 95% CI of PR is estimated using resampled 10-yr segments with replacement (see above). Based on the sensitivity test, we found that the PR estimates are largely insensitive to the segment size between 5 and 10 years (not shown).

Results.

According to the ERA5 data, the North Atlantic region had a strong NAO+ pattern during the 2019/20 winter (Fig. 1a). This strong positive NAO phase led to increases in both T2m and PREC over NW Russia (Figs. 1b,c). The regional averages are consistent between the CRU gridded data and station observations (see white dashed lines in Figs. 1d,e). The CMIP6 simulations show a wide range of year-to-year fluctuations of T2m (−10° to +10°C) and PREC (−0.8 to +0.8 mm day$^{-3}$) anomalies, indicating that internal variability can play a role in generating extreme climatic events over the study region. The CMIP6 H-forcing simulations show consistency with observed anomalies, with similar interannual variability ranges of T2m and PREC. The MMMs of H-forcing runs exhibit linear trends of T2m and PREC since emerging around 1960 and 1970, respectively, indicating the growing anthropogenic impacts on the regional extreme climatic events over NW Russia over time.

The NW Russia had anomalously high T2m (+6.9°C) and PREC (+0.6 mm day$^{-3}$) during the 2019/20 winter (Figs. 1f,g). The MMM values from H-, G-, N-, and A-forcing runs show anomalies with the corresponding magnitudes of +42%, +47%, +4%, and −13% (+32%, +26%, −4%, and −7%) of the observed T2m (PREC) anomaly. The NAO index in 2019/20 explains the observed T2m and PREC anomalies by 37% and 23%, respectively, while NAO shows a significant correlation with wintertime T2m and PREC anomalies over NW Russia (0.7 and 0.46, respectively) during 1951–2020. The 95th percentile ranges of T2m (27.5%–46%) and PREC (12%–33%) are wider in the A- and H-forcing runs, respectively, than those in other forcing runs, indicating possible differences in T2m and PREC sensitivity to the aerosol forcing.

We counted the events of exceeding the observed T2m and/or PREC anomalies in the 2019/20 winter from the 10-yr segments of CMIP6 simulations. The 10-yr sample segments of H-, G-, N-, and A-forcing runs include 760, 650, 740, and 680 values, respectively. From the segments for the 2010s, the numbers of events exceeding the observed T2m (PREC) anomaly are 31, 76, 4, and 2 (38, 41, 1, and 1) for the H-, G-, N-, and A-forcing runs, respectively. We found 7 and 17 events of simultaneously exceeding the observed T2m and PREC anomaly in

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3 www.cpc.ncep.noaa.gov/products/precip/CWlink/pna/norm.nao.monthly.b5001.current.ascii.table
the H- and G- forcing runs, respectively. Sensitivity tests using the model samples with positive NAO phases indicate that warm-wet extremes occur more frequently due to the global warming influences (see heading S3 in the online supplemental material).

The segments for 1990s show a decreased number of the exceeding events as 18, 30, 6, and 1 (17, 27, 3, and 1) extreme cases for the H-, G-, N-, and A-forcing runs for T2m (PREC), respectively. We found four and six joint exceeding events of T2m and PREC anomalies in the H- and G-forcing runs for the 1990s, respectively. The results indicate that the anthropogenic forcing with emerging signal since the 1960s has increased the likelihood of warmer or wetter winter and that a 2019/20-like exceptionally anomalously wet and warm winter would have been extremely unlikely without human influences, particularly anthropogenic greenhouse gas increases.

For visualization, we fitted the Gaussian functions to multimodel T2m and PREC data from each forcing runs for 1990s and 2010s (Figs. 2a–d). Overall, the anthropogenic influence increased the likelihood of the extremely warm or wet winter in 2019/20 significantly because the warming or wetting response to G-forcing surpasses the cooling or drying response to A-forcing.

Fig. 2. Fitted Gaussian distributions of simulated (a) T2m and (c) PREC anomalies for 1990s (dotted lines) and 2010s (solid lines) by H- (orange line) and N- forcing (blue). (b),(d) The fitted distributions in (a) and (c), respectively, are zoomed in near the observed threshold values. (e) Circles and bars depict the median and 95th percentile range (2.5th–97.5th percentile) of PR values from the 1,000 bootstrapping 10-yr segment samples for the 1990s (dotted lines) and 2010s (solid lines).
Based on the order statistics, the estimates of $P_{H}/P_{N}$, $P_{C}/P_{N}$, and $P_{A}/P_{N}$ for warm winter from the 10-yr segment for the 2010s (1990s) are 6.2 (3), 19.4 (6.6), and 0.4 (0.2) (Fig. 2e). The estimates of $P_{H}/P_{N}$, $P_{C}/P_{N}$, and $P_{A}/P_{N}$ for the 2019/20-like wet winter are 18 (4.1), 27.3 (9.7), and 0.54 (0.3). The PR for the joint event with both T2m and PREC exceeding the 2019/20 observed threshold is infinite due to no cases being found in the N-forcing runs. The results confirm that the anthropogenic forcing has increased the likelihood of the 2019/20-like NW Russia winter in the last decade, suggesting more frequent warm and wet winters in the future.

In summary, the 2019/20 NW Russia winter was the warmest and wettest on record since 1902. Based on the 12 CMIP6 model simulations, which can reproduce the observed T2m-PREC seasonal cycles, H- and G-forcing have likely contributed to the increased probability of such warm (wet) winter, by a factor of 6.2 and 19.4 (18 and 27.3), respectively. In particular, the events of simultaneously exceeding the observed T2m and PREC anomalies in the 2019/20 winter were found only in the H- and G-forcing runs. These findings are in line with the CMIP6-based assessment of Ciavarella et al. (2021), who found that prolonged Siberian heat during January–June 2020 would have been almost impossible without human influence. It is concluded that the 2019/20 unusual warm and wet winter over NW Russia is strongly attributable to anthropogenic warming, surpassing the naturally driven ranges.

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References
Were Meteorological Conditions Related to the 2020 Siberia Wildfires Made More Likely by Anthropogenic Climate Change?

Zhongwei Liu, Jonathan M. Eden, Bastien Dieppois, Igor Drobyshev, Carolina Gallo, and Matthew Blackett

The summer of 2020 saw Siberia hit by widespread wildfires for a second consecutive year. By September alone, 14 million hectares had been burnt by more than 18,000 individual fires (Witze 2020). The 2020 fires were responsible for the emission of approximately 350 megatons of carbon, more than 4 times the annual average observed across Siberia during the preceding two decades (Ponomarev et al. 2021). While fire activity is common in Siberia, accounting for between 8.5% and 25% of annual burned area worldwide (Kharuk et al. 2021), it was the dominance of fires at northerly latitudes that made the 2020 event truly exceptional. Fires beyond 65°N typically account for <10% of Siberia’s annual total burned area, but their contribution during 2020 exceeded 25%, the largest observed since 2001 (Conard and Ponomarev 2020), promptly raising concerns about the growing influence of wildfires on permafrost thaw (Kim et al. 2020) and greenhouse gas emissions (Ponomarev et al. 2021).

During 2020, spring and summer temperatures were abnormally high across Siberia. At Verkhoyansk in Yakutia (67°33’N, 133°23’E), a new record of 38°C was set for the highest daily maximum temperature ever recorded north of the Arctic Circle (WMO 2020). A comprehensive
study conducted by the World Weather Attribution consortium concluded that such intense temperature, spanning such a large area, would have been almost impossible during the first half of 2020 without the influence of human-induced climate change (Ciavarella et al. 2021).

While this period of extreme heat was undoubtedly an important factor driving wildfire activity, a specific assessment of the contribution of human-induced climate change should account for other meteorological factors that collectively present fire-conducive conditions. Such an assessment is made challenging by Siberia’s vast geographical extent and varied climatology (de Groot et al. 2013; Samsonov and Ivanova 2014). Here, we isolate Siberia’s most intense fire episodes during 2020 and quantify the influence of global warming on the meteorological conditions associated with each. The collective analysis of a series of individual events that formed part of a larger phenomenon constitutes a unique aspect of this study. In our analysis of individual fire hotspots, we maintain a consistent spatiotemporal event definition, allowing for comparisons of results at different hotspots.

**Data and methods.**

Throughout the study, fire-conducive meteorological conditions are defined by the Canadian Fire Weather Index (FWI; Van Wagner 1987), a widely used metric based on relative humidity, surface wind speed, precipitation, and temperature to quantify forest fire danger. It forms the basis of global fire weather datasets (Field et al. 2015; Vitolo et al. 2020) and the Global Wildfire Information System. Our study region is defined by the west, east, and northeast Siberian taiga ecoregions (Olson et al. 2001), which collectively constitute an area of 6,700,000 km² and represent some of the most extensive areas of natural forests in the world. The location and intensity (defined by fire radiative power) of fire events during the April–September 2020 fire season were determined using satellite-derived data from the Visible Infrared Imaging Radiometer Suite (Schroeder et al. 2014), made available via the Fire Information for Resource Management System (FIRMS). Historical FWI data for the period 1979–2020 are taken from the global fire danger reanalysis (0.25° resolution; Vitolo et al. 2020) produced by the Copernicus Emergency Management Service for the European Forest Fire Information System. Simulations of historical FWI data for the period 1880–2014 (~0.7° resolution) are taken from the CNRM-CM6-1 general circulation model (Voldoire et al. 2019) developed for phase 6 of the Coupled Model Intercomparison Project (CMIP6; Eyring et al. 2016). This model is chosen due to 1) the availability of a relatively large (30 member) ensemble and 2) its capacity to realistically represent extreme FWI statistics across Siberia (Gallo Granizo et al. 2021).

We conduct independent attribution analysis at a series of 13 “hotspots” associated with the most intense 2020 fires (see the online supplemental material for details). The “2020-type event” is defined at each hotspot as the April–September maximum value of 7-day mean FWI (hereafter FWIX7day) occurring within the hotspot’s spatial domain. A statistical method based on a time-dependent generalized extreme value (GEV) distribution, frequently applied to both observational and climate model data in previous work (e.g., Schaller et al. 2014; Eden et al. 2016; van der Wiel et al. 2017; Eden et al. 2018; Otto et al. 2018; Krikken et al. 2021), is used to estimate the change in probability of a 2020-type event as a result of global warming. For each hotspot, a pool of spatial maxima in FWIX7day from all 135 years and all 30 ensemble members are fitted to a GEV distribution in which the location \( \mu \) and scale \( \sigma \) parameters are assumed to scale linearly with 4-yr smoothed global mean surface temperature (GMST; GISTEMP Team 2021; Lenssen et al. 2019). Both the shape \( \zeta \) parameter and the \( \sigma/\mu \) ratio remain constant (Philip et al. 2020).

At each hotspot, we evaluate the return time, and hence the probability, of a 2020-type event occurring in a “past” climate of 1880 (\( p_p \)) and a “present” climate of 2020 (\( p_p \)). Changes in likelihood of 2020-type events are quantified using the probability ratio (PR) \( p_o/p_p \). We also calculate the percentage change in FWI magnitude (%MAG) between a 2020-type event and...
Results.

Fires were widespread throughout the study region during April–September 2020 (Fig. 1a). The most intense fires occurred in several clusters and generally north of 60°N. The highest-intensity fires were detected throughout the fire season, with a large proportion occurring between mid-June and August (Fig. 1b). The individual fire detections at the center of each hotspot all reside in the upper tail of the fires’ empirical cumulative distribution function (Fig. 1c). The 2020 anomalies in FWI$^7$day were largest in central and northern Siberia, especially to the west of the Verkhoyansk mountains and across the Kolyma lowland (Fig. 1d) where a large portion of 2020 FWI$^7$day values are among the highest 5% of annual maxima observed since 1979 (Fig. 1e). At eight of the 13 hotspots, both the probability (PR > 1; Figs. ...
2a,b) and magnitude (%MAG > 0; Fig. 2c) of a 2020-type event increased between 1880 and 2020. The likelihood has increased by a factor of $1.1^{±0.1}$, corresponding to a change in magnitude of $2^{±6}$%; this is significant at the 95% confidence level at five hotspots (Figs. 2e–i). Small decreases in both probability and magnitude are found at the remaining five hotspots (Figs. 2b,c), of which only hotspot A at the western fringes of the fire-affected area is statistically significant (PR = 0.81; CI range 0.71–0.93; Fig. 2d).

Fig. 2. (a) Location of 13 fire hotspots and the overall sign change in likelihood of a 2020-type event between 1880 and 2020 (red: increase; blue: decrease; solid lines: significant; dashed lines: not significant). (b) PR calculated at each hotspot; bars show 95% CIs following non-parametric bootstrapping; central value shown in bold. (c) As in (b), but for %MAG. (d–i) Gumbel plots for significant hotspots, showing the GEV model fit scaled to the smoothed GMST of 1880 (blue) and 2020 (red). Shading represents the 95% CIs. The magenta lines represent the 2020 FWIx7day events, scaled to the model distribution using bias correction. The blue (red) bars represent the 95% CIs for the return period of a 2020-type event in the climate of 1880 (2020).
Positive changes in likelihood are found at the four hotspots (labeled C, H, K, and M) residing north of 65°N, where the exceptionality of 2020 fire weather is evidenced by large anomalies (>10 FWI units) amounting to some of the highest of FWIx7 day values observed since 1979 (Figs. 1d,e). At hotspot C, the likelihood of a 2020-type event is found to have increased by more than 30% (PR = 1.33; CI range of 1.10–1.55; Fig. 2e). A change of almost 20% is found at hotspot H, but is not significant at the 95% level. Farther east, significant increases in likelihood are found at hotspots K and M and, farther south, L (Figs. 2g–i). At hotspot K, which represents an area of the Kolyma lowland that witnessed several extreme fires (FWP > 700 MW; Fig. 1a), a 2020-type event has become almost 80% more likely since 1880 (PR = 1.78; CI range of 1.22–2.58; Fig. 2g). Significant, though smaller, increases are found at hotspots L (PR = 1.57; CI range of 1.29–1.1; Fig. 2h) and M (PR = 1.15; CI range of 1.02–1.28; Fig. 2i). FWI extremes across the eastern region are likely to be linked to episodes of extreme heat across northern Siberia, but further analysis would be required to connect the attribution of FWI maxima at these hotspots to that of the distribution of extreme heat during the first half of 2020 (Ciavarella et al. 2021).

Hotspots west of the Verkhoyansk range are not associated with significant increases in likelihood despite being representative of the most intense fire clusters across the central Siberian plateau. At hotspots B and E, which correspond to areas of particularly intense fires and large FWI anomalies during 2020, the likelihood of 2020-type conditions was found to have decreased by approximately 10%–20% (not significant at the 95% level). The increase in likelihood of more than 20% (PR = 1.21; CI range 1.03–1.46) at the most southerly hotspot, D, is striking given that it is unlikely to be linked explicitly to the extreme heat in the north (Fig. 2f).

Conclusions.
Our analysis has sought to quantify the role of human-induced climate change on fire meteorological conditions associated with the most intense fire episodes occurring in Siberia over the 2020 fire season. Previous work has identified the fingerprint of human influence on the extreme heat during the beginning of the year (Ciavarella et al. 2021). To complement such work, we considered the link between long-term global temperature and the meteorological parameters that collectively constitute extreme fire weather. We applied an established statistical method to output from CNRM-CM6-1 to quantify the long-term influence of global temperature trends on annual fire weather maxima separately at a series of regions experiencing the most intense fire activity. By averaging the results at different hotspots, we found that fire weather extremes are (i) around 10% more likely across the study region on average and (ii) up to 80% more likely in northeast Siberia, as a result of global warming.

The inter-hotspot differences are intriguing and merit further analysis to quantify the factors that contribute toward trends in extreme fire weather in this vast region. More generally, the results highlight the sensitivity of the findings of wildfire attribution analysis to the spatiotemporal characteristics used to define the event, either in terms of the impact (i.e., the fire intensity) or the prevailing meteorology (i.e., FWI). Results are also expected to be sensitive to the choice of general circulation model, which is an important additional source of uncertainty. While our analysis is based on a model that has been shown to realistically represent fire weather across Siberia (Gallo Granizo et al. 2021), further study would benefit from the inclusion of multiple models.

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References


The January 2021 Cold Air Outbreak over Eastern China: Is There a Human Fingerprint?

Yujia Liu, Chao Li, Ying Sun, Francis Zwiers, Xuebin Zhang, Zhihong Jiang, and Fei Zheng

A cold air outbreak swept across eastern China in January 2021. It is characterized as a weakened cold event that would have been more severe with less anthropogenic warming.

On 6–8 January 2021, a cold air outbreak swept across eastern China, peaking over the North China Plain the night of 6 January, when 219 weather stations recorded the lowest nighttime temperature since 1961. In total, 498 stations recorded the lowest daytime or nighttime temperature since 1961 during the 3-day event. This event, together with two other cold outbreaks that affected the region on 13–15 December 2020 and 29 December 2020–1 January 2021, led to historic peak electricity demand and resumption of the operation of the only remaining coal-fired generating plant in Beijing. This analysis puts the cold outbreak into historical perspective by considering changes in the likelihood of such events over 1961–2020 in the context of a climate that is being warmed by anthropogenic forcing.

Event definition.

We define the event using a cold-degree days (CDD) metric calculated as the cumulative sum of negative daytime maximum and nighttime minimum temperature anomalies during a cold event (in degree days, Yujia Liu, Chao Li, Ying Sun, Francis Zwiers, Xuebin Zhang, Zhihong Jiang, and Fei Zheng

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using °C), where anomalies are defined relative to 1961–90, with the climatological values for calendar days being determined using 15-day moving windows. The CDD metric is similar to the heating degree days metric, except that temperature differences from climatology are accumulated rather than differences from a fixed temperature threshold, thus minimizing the influence of biases in model-simulated CDD. CDD is related to anomalous energy consumption during a cold event.

We focus on the January 2021 event because it was the most extensive of the three cold outbreaks in the 2020/21 winter as indicated by the number of stations observing record low temperatures since 1961. The associated atmospheric circulation features include a strengthened Ural high and a deepened East Asian trough, creating circulation conditions favoring the invasion of cold air into eastern China from the Arctic (see Fig. S1 in the online supplemental material; Zheng et al. 2021).

**Data and methods.**

We acquired daily maximum and minimum temperatures from 2419 mainland China weather stations for 1961–2021. We also obtained simulations of these two variables from available climate models from phase 6 of the Coupled Model Intercomparison Project (CMIP6; Eyring et al. 2016) that provided three or more merged historical and Shared Socioeconomic Pathway 5–8.5 simulations (SSP5–8.5; O’Neill et al. 2016) and natural-forcing only simulations for 1961–2020 as of July 2021 (see Table S1 in the online supplemental material). Although the CMIP6 natural-forcing only simulations for 2015–20 are driven by the SSP2–4.5 natural forcing agents (Gillett et al. 2016), using SSP2–4.5 simulations to extend the historical simulations (which end in 2014) reduces available climate model ensemble sizes (Table S1). Nevertheless, our conclusions are qualitatively robust to the choice of SSP simulations for data extension (Fig. S2).

We computed CDD for the event and annual CDD minima (CDDn) for 1961–2020 from consecutive 3-day CDD values for individual winters at individual stations. To investigate human influence on CDD, we first aggregated station temperatures to 5° × 5° grid cell values, and then computed CDD values from the gridded values. Stations with at least 90% of daily observations for all winters in 1961–2020 were used. Temperature simulations were linearly interpolated to the same 5° × 5° grid before computing model CDD values.

We use a GEV distribution-based fingerprinting method (Zwiers et al. 2011; Wang et al. 2017) to evaluate whether human influence is discernable in the 1961–2020 CDDn observations and, if so, to quantify the human influence on the likelihood of a 3-day outbreak as cold as or colder than the 2021 event. We focus on mainland China east of 105°E, which was the region most impacted by the event. We conduct separate fingerprinting analyses for northern and southern parts of the region to accommodate their different rates of CDDn change. These analyses were conducted on the 5° × 5° grid cells marked in Fig. 1, using only those with at least 10 sufficiently complete stations.

The method fits CDDn observations at valid grid cells to GEV distributions with grid-cell-specific location, scale, and shape parameters. At each grid cell s, the location parameter varies with time as a linear function \( \mu_{s,t} = c_s + X_{s,t} \beta \) of the climate model simulated response \( X_{s,t} \) of CDDn to external forcings at that grid cell. All grid cells share the same scaling factors \( \beta \) by assuming that the model responses have the same spatiotemporal patterns as those in the observations. The model response at a given grid cell to a given external forcing is estimated as the location parameter of a GEV distribution fitted to simulations of CDDn under that forcing. Location parameters, which are assumed to vary slowly as a consequence of forcing, are constrained to be constant within 5-yr periods. Scale and shape parameters are held constant throughout the period.

Uncertainty of the scaling factor estimates \( \hat{\beta} \) due to internal variability in model responses and observations is estimated with a two-stage spatiotemporal block bootstrap procedure.
We first examine the resulting confidence intervals to determine if human influence is detected in the CDDn observations. The human influence on the likelihood and intensity of the observed event is then evaluated by comparing the estimated frequency of 3-day events as severe as the observed event during 2016–20 with that during 1961–65 and by considering changes in CDD values of 3-day events in the two periods that have the same frequency as the observed event in 2016–20.

**Results.**

_A mild 3-day cold event._ Although clusters of weather stations over regions such as the North China Plain reported record low temperatures during the event (Fig. S3), it was not a very extreme cold event on average when considering the entire northeastern and southeastern China domains. The event (Fig. 1a) occurred against a background of anthropogenic global warming. The corresponding warming of CCDn at nearly all stations (Fig. 1b) is consistent with the fact that regional CCDn values colder than observed during the 3-day event previously occurred in 27 and 52 of the 59 winters between 1961 and 2019 in northeastern and southeastern China, respectively (Fig. 1c). In northeastern China the observed event would have been considered mild during the first half of the period of record and not exceptionally cold during the second half of the period, whereas in southeastern China the event would have been considered mild throughout the period.

Fig. 1. Characteristics of the January 2021 cold event and its climate background. (a) Cold degree days observed during the 3-day cold event of 6–8 Jan 2021. (b) The 1961–2020 trends in annual minimum cold degree days of 3-day cold events (CDDn). Grid cells north and south of the white lines mark the regions of detection and attribution analyses, which are referred to as Northeast and Southeast China, respectively. (c) Time series of CDDn from 1961 to 2020 derived from regional mean daytime and nighttime temperatures of the period over (left) Northeast and (right) Southeast China, respectively. Red dashed lines show CDD values for the event, and red ticks mark years with CDDn values colder than the event value.
Human influence on observed CDDn during 1961–2020. Fingerprinting analyses (Fig. 2a) show that the climate model simulated weakening of the strength of cold events due to anthropogenic forcing is detected in the 1961–2020 CDDn observations in both northeastern and southeastern China. Detection occurs, with one minor exception, using signals estimated from either individual model ensemble simulations or multimodel ensemble simulations. The effect of natural external forcing is not detected in northeastern China except for IPSL-CM6A-LR, while it is detected in southeastern China using any of the ensembles. The natural forcing signal, which is small in all cases, cannot be detected if the anthropogenic forcing signal is not included in the fingerprinting analysis (Fig. S4). Overall, the results indicate that the observed warming of CDDn would have been unlikely in the absence of human-induced warming, thus establishing a physical basis for the attribution of the 2021 cold event.

Anthropogenic scaling factor confidence intervals for northeastern China are consistent with unity except when using signals from CanESM5 and IPSL-CM6A-LR, which are models with high climate sensitivity (e.g., Li et al. 2021). For southeastern China, anthropogenic scaling factors are consistent with unity except when using the multimodel mean signal, which appears to warm CDDn in this region significantly more slowly than observed.
Human influence on the 2021 cold event. The fingerprinting exercise provides observationally calibrated time-evolving GEV distributions conditional on model-simulated CDDn that can be used to estimate changes in the frequency and intensity of 3-day cold outbreaks caused by external forcing. Using the distributions conditional on the multimodel mean CDDn, we find that the likelihood of observing a cold event that is as cold or colder than the 2021 event was about 2.0 times as likely in 1961–65 than in 2016–20 in northeast China and perhaps 1.2 times as likely in southeast China (Fig. 2b; purple lines). Correspondingly, 3-day cold events with the estimated frequency of the 2021 event were roughly 9.0 degree-days colder during 1961–65 than during 2016–20 (green lines; Fig. 2b). Even though the event was regarded as being extreme and impactful, it evidently would have been substantially more intense in the absence of the warming that has occurred over the past 60 years. Uncertainties are large in part because our inferences are made on a grid box scale comparable to or smaller in size than that of the majority of Chinese provinces, which is the scale on which decision making on climate adaptation often occurs.

Summary. We analyzed the 3-day January 2021 cold event in China and its historical climate change background using a novel cold degree days metric in combination with a fingerprinting analysis technique designed specifically for extremes. Despite high impacts and the setting of a large number of cold temperature records, this was a relatively mild event regionally, with clear evidence that human influence on the climate has reduced the strength and probability of such events since 1961. Nevertheless, our inferences, which are made at the $5^\circ \times 5^\circ$ scale using different model ensemble simulations, are relatively uncertain and should be used qualitatively. Studies have reported that the weakened winter Northern Hemisphere meridional temperature gradient (Ding et al. 2008) and Arctic sea ice loss (Mori et al. 2019) caused by anthropogenic warming may have induced more cold air outbreaks. Our results support the idea that anthropogenic warming has warmed cold outbreak events. Nevertheless, their impacts to, for example, people’s perception of cold and heating energy demand, which are also affected by changes in exposure and vulnerability, may not have diminished accordingly.

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References
The Contribution of Human-Induced Atmospheric Circulation Changes to the Record-Breaking Winter Precipitation Event over Beijing in February 2020

Lin Pei, Zhongwei Yan, Deliang Chen, and Shiguang Miao

During February 2020, North China observed unusually high precipitation, with many stations receiving total monthly precipitation exceeding 300% more than the 1981–2010 climatology for February (Fig. 1). In particular, Beijing received a historical record of 27.8 mm of precipitation (Fig. S1a), which is 592% more than the long-term mean. The combined influences of snow, low temperatures, and frost hazards in this period posed serious challenges to this megacity of over 20 million people, with various socioeconomic impacts and serious effects on transportation and electricity power.

Few attribution analyses have considered regional extreme precipitation events during winter in China (Zhao 2020). The extreme precipitation in February 2020 over Beijing raises questions about whether anthropogenic influences have affected the frequency of such events. However, there are some common deficiencies in reproducing extreme precipitation indices over China in global climate models (GCMs). For example, in the

Precipitation in Beijing during February 2020 was the highest since 1951. Anthropogenic influences contributed to a 52.9% increase in the likelihood of circulation anomalies associated with similar extreme precipitations.
CMIP5 simulations, the areal-mean biases for total precipitation, heavy precipitation, and precipitation intensity over China are 127%, 87%, and 22%, respectively (Zhu et al. 2020). It is difficult to directly attribute such local extreme precipitation events using model outputs at coarse resolution (Trenberth et al. 2015; Zhai et al. 2018; Chen et al. 2020; Sun et al. 2021). However, recent studies have conducted attribution analyses of regional extreme events from the perspective of the dominant circulation patterns, also finding human influences to be mainly responsible for changes in these extremes (Horton et al. 2015; Pei and Yan 2018; Zhou et al. 2020). Harrington et al. (2016) demonstrate the utility of an approach in characterizing the meteorological conditions conducive for an extreme drought event in 2013 over New Zealand and identify a robust increase in the likelihood of the observed circulation patterns like...
those of the 2013 drought in the recent-climate simulations. In a large ensemble of climate model simulations, Schaller et al. (2016) find that anthropogenic warming causes a small but significant increase in the number of January days with the westerly flow, which increases extreme precipitation over southern England. Therefore, this study examines the change in frequency of circulation patterns related to extreme precipitation during February in Beijing.

Data and method.

The observed and reanalysis datasets used in this study are as follows. 1) Monthly homogenized precipitation observations at 2414 stations in China for 1951–2020 provided by the China Meteorological Administration (http://data.cma.cn/); there are 20 stations in the Beijing area. 2) Monthly circulation data comprising wind speed, geopotential height, and relative humidity covering 1951–2020, obtained from NCEP–NCAR at 2.5° resolution (Kalnay et al. 1996). 3) Monthly circulation data for 1900–2010 from the Twentieth Century Reanalysis version 2 (20CR) at 2° resolution (Compo et al. 2011) and from the ECMWF Atmospheric Reanalysis for the twentieth century (ERA20C) at 1° resolution (Poli et al. 2016).

Monthly circulation simulated by 20 runs of 7 CMIP5 models contributing to the All-Hist, Nat-Hist, and RCP8.5 experiments (see Table S1 in the online supplemental material) obtained from CMIP5 (Taylor et al. 2012) are also used. The All-Hist simulations are forced by natural (solar radiation and volcanic aerosols) and anthropogenic agents (greenhouse gases, aerosols, ozone, and land use), while the Nat-Hist simulations are forced only by natural agents. The RCP8.5 simulations are run with the projected increases in the atmospheric concentration of greenhouse gases, representing the uncontrolled high-emissions scenario.

We applied an approach used in similar studies (Ren et al. 2020; Zhou et al. 2020). We identify the circulation anomaly related to extreme winter precipitation in Beijing using the atmospheric reanalyses and examine how anthropogenic influences alter the probability of such circulation patterns using the ensembles of CMIP5 models.

Results.

Atmospheric circulation conditions related to extreme winter precipitation over Beijing and its changes in the twentieth century. We calculated the correlation between precipitation over Beijing and anomalies in atmospheric circulation for February in the period from 1951 to 2020. Strong correlation is found in geopotential height at 500 hPa, meridional wind at 850 hPa, and relative humidity near the surface (Figs. 1d–f). When precipitation over Beijing is anomalously high, there is an anomalous anticyclonic system over the western Pacific, resulting in a shallow East Asian trough, which represents a weakened East Asia winter monsoon (EAWM) (Jhun and Lee 2004; Pei et al. 2018). This anomalous anticyclonic system can be seen in the regional mean of the geopotential height within 29°–46°N, 123–171°E (green box in Fig. 1d), hereafter referred to as H500. Under these conditions, the western Pacific region along the east coast of China experiences widespread anomalous southerlies in the lower troposphere (Fig. 1d), favorable for the transportation of warm and humid air from the northwestern Pacific into adjacent regions, including northern China, the Korean Peninsula, and southern Japan. A practical index for measuring the strength of the EAWM is the meridional wind speed anomaly at 850 hPa over the northwestern Pacific (17°–41°N, 114°–144°E: green box in Fig. 1e), referred to as V850. As a result, abundant moist air is transported into North China, resulting in abnormally high levels of relative humidity over this region, thereby inducing conditions favorable to extreme winter precipitation (Fig. 1f). The humidity conditions are captured as the regional mean relative humidity within 26°–42°N, 110°–161°E (green box in Fig. 1f), hereafter referred to as RH1000.

The correlation coefficients between February precipitation in Beijing and the H500, V850, and RH1000 indices for 1951–2020 are all significant under the t test ($\alpha = 0.01$) (Fig. 1b). Favorable circulation conditions occur concurrently and promote extreme precipitation events
in Beijing. We normalize each time series by its respective standard deviation for 1971–2000 and apply a multiple linear regression (MLR) model to construct a compound index. The MLR equation is \( y = 0.019 + 0.308 \times RH1000^* + 0.103 \times V850^* + 0.315 \times H500^* \), with asterisks (*) representing normalized series. This new index is normalized to its climatology and is referred to as the circulation index (CI; red line in Fig. 1b), with a significant correlation coefficient (Corr = 0.58) to winter precipitation in Beijing for 1951–2020. We also examine a suite of other relevant variables but find that adding more circulation variables does not markedly change the correlation because the effect of the other variables is implicitly included in the CI through their correlation with the three dominant variables. The CI reached 2.21\( \sigma \) in February 2020, second to only one stronger event in 1990 (Fig. 1b). Total precipitation over the North China during 1990 was 26.8 mm, the highest since 1951 (Fig. S1a), and the precipitation center was located in the southern part of North China rather than the Beijing area (Fig. S1b). Therefore, winter circulation anomalies for February 2020 can be treated as an extreme climate event (corresponding to a CI equal to or greater than 2.21\( \sigma \)).

Based on long-term reanalysis, the probability of extreme atmospheric circulation anomalies (i.e., those with a CI value greater than 2.21\( \sigma \)) increased twofold in the twentieth century (Fig. 1c), from a once-in-50-year event during 1901–1950 to a once-in-25-year event during 1951–2000 (Table 1). There is also a consistent shift in the frequency of the three components that make up CI (i.e., H500, V850, and RH1000) (Fig. S2). The probabilities of extreme values of these components (H500, V850, and RH1000), such as those occurring in 2020, increased from the first half to the second half of the last century by between 20\% and 166\% (Table 1). The increase in frequency is statistically significant, but the role of anthropogenic influence remains to be clarified.

Table 1. The frequency of extreme winter atmospheric circulation anomalies (CI, RH1000, V850, and H500) was stronger than that of the 2020 event in the reanalysis data (20CR and ERA20C) and simulations (CMIP5). Here \( \sigma \) = standard deviation of the time series for 1971–2000. Values of changes are in bold.

<table>
<thead>
<tr>
<th></th>
<th>Frequency</th>
<th>RH1000</th>
<th>V850</th>
<th>H500</th>
<th>CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cir (2020)</td>
<td>2.21( \sigma )</td>
<td>0.77( \sigma )</td>
<td>1.03( \sigma )</td>
<td>2.21( \sigma )</td>
<td></td>
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<tr>
<td>20CR</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>1901–1950</td>
<td>0</td>
<td>26.0%</td>
<td>6.0%</td>
<td>2.0%</td>
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<tr>
<td>1951–2000</td>
<td>0</td>
<td>32.0%</td>
<td>16.0%</td>
<td>4.0%</td>
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</tr>
<tr>
<td>Change</td>
<td>—</td>
<td>23.0%</td>
<td>166.0%</td>
<td>100.0%</td>
<td></td>
</tr>
<tr>
<td>ERA-20c</td>
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<tr>
<td>1901–50</td>
<td>0</td>
<td>16.0%</td>
<td>10.0%</td>
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<tr>
<td>1951–2000</td>
<td>0</td>
<td>24.0%</td>
<td>12.0%</td>
<td>4.0%</td>
<td></td>
</tr>
<tr>
<td>Change</td>
<td>—</td>
<td>50.0%</td>
<td>20.0%</td>
<td>—</td>
<td></td>
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<tr>
<td>Simulations</td>
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<td></td>
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<tr>
<td>from 20 CMIP5</td>
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<td>model runs</td>
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<td>Nat-Hist: 1951–2000</td>
<td>1.3%</td>
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<td>5.2%</td>
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<tr>
<td>RCP8.5: 2050–99</td>
<td>2.6%</td>
<td>29.8%</td>
<td>26.7%</td>
<td>9.6%</td>
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<tr>
<td>Change (All-Hist–Nat-Hist)</td>
<td><strong>38.5%</strong></td>
<td><strong>19.4%</strong></td>
<td><strong>58.9%</strong></td>
<td><strong>52.9%</strong></td>
<td></td>
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<tr>
<td>Change (RCP8.5–All-Hist)</td>
<td><strong>44.4%</strong></td>
<td><strong>18.3%</strong></td>
<td><strong>86.7%</strong></td>
<td><strong>84.7%</strong></td>
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</tbody>
</table>
Anthropogenic influence on the occurrence of extreme winter circulation conditions. To construct the CI series in the historical and future simulations, the normalized anomalies of H500, V850, and RH1000 are calculated based on the All-Hist 30-yr (1971–2000) climatology for each model. There is a remarkable shift toward higher CI values in the All-Hist and RCP8.5 simulations compared with the CI distribution in the Nat-Hist simulations, with a 32% and 68% increase in the mean relative to the standard deviation, respectively (Fig. 2a). There are consistent changes in the component indices in the All-Hist and RCP8.5 scenario toward a more frequent occurrence of the anomalous anticyclonic system over the northwestern Pacific in the midtroposphere, weakened EAWM (with anomalous southeasterly flows), and abnormally high relative humidity in the Beijing area (Figs. 2b–d). The probability of atmospheric circulation anomalies conducive to extreme winter precipitation in Beijing (CI larger than 2.21σ) changes from 3.4% under the Nat-Hist scenario to 5.2% under the All-Hist scenario and further increases to 9.6% in the future scenario (Table 1). This finding suggests that anthropogenic influence has contributed to an approximately 52.9% increase in the likelihood of such circulation anomalies causing extreme winter precipitation, and the models project a further 84.7% increase under the RCP8.5 scenario. These results are supported by strong intermodel agreement, as 19 out of 20 runs reproduced an increased frequency of atmospheric circulation anomalies with positive CI values (Table S1).

Conclusions.
Beijing experienced its wettest February in 2020 since at least 1951, but it is challenging to directly attribute such precipitation local extremes using only climate models. Here, employing both observations and climate model simulations, we analyzed the anthropogenic influence on the changes in the likelihoods of atmospheric circulation conditions related to very wet February conditions. Similar extreme precipitation events are associated with an anomalous anticyclone over the northwestern Pacific and a weakened EAWM, resulting in above-average relative humidity in the Beijing area. According to reanalysis data, such circulation anomalies have increased in frequency by approximately 100% in the twentieth century. Finally, in an ensemble of 20 runs of CMIP5, we find that anthropogenic influence has caused a 52.9% increase in the likelihood of such extreme circulations, and we project a further 84.7% increase under the RCP8.5 scenario.

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References


Attribution of April 2020 Exceptional Cold Spell over Northeast China


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Human-induced thermodynamic effects have declined the likelihood of April 2020-like cold spells over Northeast China by ~80%, but such events tend to be triggered by more intense dynamical factors.

Northeast China (105°–135°E, 37°–55°N) is an important agricultural production area for wheat, soybean, and maize, among other crops (Lu et al. 2017; http://country.cnr.cn/gundong/20160303/t20160303_521524231_1.shtml), making a substantial contribution to the food security of China. Late boreal spring (mid-April to mid-May) is a transition period when most crops are at their critical growing stage. Under climate change, a widespread shift toward earlier spring greening, triggered by warmer temperature, has been documented (Schwartz et al. 2006; Piao et al. 2015; Tan et al. 2018). Extreme cold events occurred at growth stage are more likely to cause serious damage to crop yields and large economic loss (Wheeler et al. 2000; X. Li et al. 2015).

In the recent decades, regional cold extremes, superimposed on a warmer climate, recurred throughout the Northern Hemisphere (Cattiaux et al. 2015; Qian et al. 2018; Christidis and Stott 2020; Zhang et al. 2021). April 2020 was the second hottest April (following April 2016) in the records, being 1.06°C above the twentieth-century average (www.noaa.gov/news/april-2020-was-earth-s-2nd-hottest-april-on-record). However, Northeast China witnessed an exceptional cold spell from 19th to 25th April 2020, mainly affecting the provinces of Heilongjiang, Jilin, Liaoning, Inner Mongolia, Hebei,
and Shanxi (Guan et al. 2020). The regionally averaged daily mean temperature anomaly during the coldest 5 days (20–24 April 2020) exceeded $-5^\circ$C with respect to the normal level (Fig. 1a), and some stations were even below $-7^\circ$C (Fig. 1b). More than 4 million people and 530,000 ha of crop area were impacted by this extremely cold event, resulting in a total direct economic loss of 8.2 billion RMB (www.mem.gov.cn/xw/yjglbgzdt/202101/t20210102_376288.shtml). This event was one of the top 10 natural hazard events in China for 2020 (www.cma.gov.cn/2011xwzx/2011xmtjj/202101/t20210104_569543.html) due to its agricultural damage.

Recent attribution studies addressed that anthropogenic forcings have basically reduced the likelihood of extremely cold waves (Qian et al. 2018; Christidis and Stott 2020; Duan et al. 2021; Zhou et al. 2021). It remains insufficient in elaborately documenting the human-induced thermodynamic and dynamical effects on such cold events. Here, we attempt to investigate the changing probability of April 2020–like cold spells over Northeast China due to anthropogenic forcings from both thermodynamic and dynamical perspectives. Our results should provide a comprehensive insight into human influences on cold extremes in a warming climate.

Data and methods.

We used daily mean temperatures from nearly 200 stations over the study region (Fig. 1b) for 1961–2020. This observational dataset is homogenized and provided by the National Meteorological Information Center of China (Z. Li et al. 2015). The atmospheric circulations were depicted using daily data from the ERA5 reanalysis at a horizontal resolution of 0.25° (Hersbach and Dee 2016). To be consistent, observation and reanalysis data were interpolated into the model resolution (0.56° × 0.83°) using the iterative improvement objective analysis and bilinear interpolation [available in NCAR Command Language (NCL); www.ncl.ucar.edu/], respectively.

Considering the significant impacts of continuous low temperature on agriculture (X. Li et al. 2015) and following the definition of spring cold spells in Zhu et al. (2018), we characterized spring extremely cold events as the minimum value of 5-day running mean of daily mean temperature anomalies (TA5) for 16 April–15 May. To remove the seasonal variations of temperature during the transition period, anomalies were calculated with respect to the daily mean climatology for 1981–2010.

At synoptic scale, the April 2020–like cold spells over Northeast China are closely associated with an anomalous dipole pattern of geopotential height at 500 hPa (Zhu et al. 2018). Thus, we defined a circulation strength index (CSI) as the difference of regional-averaged 500-hPa geopotential height between the Ural ridge (80°–115°E, 50°–65°N) and the East Asian trough (115°–150°E, 35°–50°N), identified according to ERA5 reanalysis (Fig. 1d). A positive index means a meridional circulation with anomalous northerlies prevailing between the two regions from the geostrophic wind balance, which favors the transport of cold air into Northeast China (Guan et al. 2020). Significant ($p < 0.01$) correlations between the regionally averaged TA5 and the corresponding CSI further demonstrate their reasonability (figures not shown). For slight displacements in the anomalous centers compared with the ERA5 observations (see Fig. ES2 in the online supplemental material), the simulated CSI was calculated according to the adjusted regions 75°–110°E, 55°–70°N and 110°–145°E, 40°–55°N. In the attribution analysis of the April 2020–like cold extremes, TA5 and CSI represented the thermodynamical and dynamical factors, respectively.

The HadGEM3-GA6-based attribution system (Christidis et al. 2013; Ciavarella et al. 2018) at a resolution of 0.56° × 0.83° was used to investigate the anthropogenic influences on the changing probability of the April 2020–like cold extreme over Northeast China. Here, ensembles of simulations from the HadGEM3-A-N216 atmosphere model were used to estimate the frequencies of extremes with and without human influences. First, a 15-member ensemble of historical simulations (Historical) for 1961–2013, driven by both natural (solar variability and volcanic eruptions) and anthropogenic forcings (greenhouse gases, aerosols, ozone, and
land use), was compared with observations to evaluate the model’s performances. A Kolmogorov–Smirnoff (K-S) test was applied to test if the distributions of the observations and Historical simulations are from the same population. Then, two 525-member ensembles of simulations for 2020 only, with different specifications of climatic forcings, sea surface temperatures (SSTs), and sea ice, were applied to estimate the probability of the April 2020–like cold events. One ensemble was forced as the Historical simulations (HistoricalExt), and the other was forced by climatic forcings without human influences, comprising the preindustrial atmospheric forcing and SSTs and sea ice with anthropogenic contributions removed (HistoricalNatExt).

For a better performance (figures not shown), a gamma distribution was fit to the indices for each ensemble of simulations and observations. The probabilities of exceeding the threshold of cold events with (HistoricalExt) and without (HistoricalNatExt) anthropogenic forcings were denoted as \( P_{\text{ALL}} \) and \( P_{\text{NAT}} \), respectively. Then, the risk ratio (RR) was calculated as \( P_{\text{ALL}}/P_{\text{NAT}} \) (National Academies of Sciences, Engineering, and Medicine 2016). The 90% confidence interval uncertainty (90% CI) for RR was estimated by bootstrapping (sampling with replacements; Efron and Tibshirani 1993).

Fig. 1. (a) Observed running pentad-mean temperature anomaly (TA5; °C) averaged over Northeast China during 16 Apr–15 May 2020, relative to the daily mean climatology for 1981–2010. Each value is indexed by the middle day of the pentad. (b) Observed TA5 (°C) for 20–24 Apr 2020. Shading is TA5 based on the gridded observations. Dots are the percentile ranks of minimum TA5 for 16 Apr–15 May 2020 during 1961–2020 at each station. (c) Return periods of minimum regional TA5 for 16 Apr–15 May during 1961–2020. (d) 500-hPa geopotential height (contours; gpm) and anomalies (shadings; gpm), for 20–24 Apr 2020, relative to the monthly mean climatology for 1981–2010. Gray boxes indicate the regions of the Ural ridge (80°–115°E, 50°–65°N) and East Asian trough (115°–150°E, 35°–50°N).
Fig. 2. (a) Time series of minimum TA5 (°C) for 16 Apr–15 May for observations (black; 1961–2020) and Historical simulations (1961–2013). The ensemble mean and spread are illustrated by the red line and pink shadings. (b) Gamma-fitted probability density function (PDF) and histograms of minimum TA5 for 16 Apr–15 May for observations and Historical simulations. (c) Gamma-fitted PDF and histograms of minimum TA5 and (d) corresponding circulation strength index (CSI) for 16 Apr–15 May based on HistoricalExt (red) and HistoricalNatExt (blue) simulations for 2020. The vertical lines in (c) and (d) indicate the minimum TA5 and CSI of April 2020 event. Also shown are gamma-fitted PDF and histograms of monthly (16 Apr–15 May) mean (e) temperature and (f) CSI in HistoricalExt and HistoricalNatExt simulations.
Results.

The overlapping TA5 during 16 April–15 May 2020 shows that the coldest 5 days occurred on 20–24 April (Fig. 1a). During these 5 days, nearly half of the stations in Northeast China experienced a record-breaking cold event (Fig. 1b). The recorded lowest TA5 was below –7°C. The regionally averaged TA5 exceeded –5°C, with a return period of about 1 in 20 years (Fig. 1c). This cold extreme was accompanied by positive and negative geopotential height anomalies at 500 hPa over western Siberia and East Asia, respectively, with prevailing anomalous northeasterlies between the two regions (Fig. 1d).

Model performance was evaluated by comparing the annual time series of minimum TA5 for 16 April–15 May from observations and the 15-member ensemble of Historical simulations (Fig. 2a). HadGEM3-A-N216 basically reproduces the temporal evolution for the April 2020-like cold events, and the observational range is within the model spreads. The probability density functions (PDFs) of the minimum TA5 for 16 April–15 May for observations (1961–2020) and historical simulations (1961–2013) are also highly comparable, confirmed by the K-S test ($p = 0.55$; Fig. 2b). Therefore, the HadGEM3-A-N216 simulations are reliable enough to conduct further attribution analysis.

First we examine the thermodynamic effects of anthropogenic forcings on the April 2020–like cold events. The PDF of the minimum TA5 shifts toward a warmer condition for HistoricalExt simulations compared to HistoricalNatExt simulations for 2020 (Fig. 2c), indicating that the probability of cold events tends to decline due to human influences. The minimum TA5 based on the observation (–5.2°C) was used as a threshold to define the April 2020–like cold event. The probability of 2020-like cold extremes is $-14.3\%$ [90% confidence interval (CI) 12.1%–16.4%] for HistoricalNatExt simulations, while it is 2.4% (90% CI 1.6%–3.4%) for HistoricalExt simulations. Thus, RR is 0.17 (90% CI 0.11–0.25), indicating that anthropogenic forcings have decreased the likelihood of April 2020–like cold events over Northeast China by ~80%. Correspondingly, the return period of such cold events has increased from ~1 in 7 years for HistoricalNatExt simulations to ~1 in 40 years for HistoricalExt simulations (Fig. ES1).

We further investigate the human-induced dynamical impacts on the April 2020–like cold events. The differences in 500-hPa geopotential height during such cold extremes (minimum TA5 less than –5.2°C) between HistoricalExt and HistoricalNatExt simulations present positive anomalies over western Siberian region while negative anomalies over the Northeast China (Fig. ES2), with a slight displacement compared with the ERA5 observations (Fig. 1d). As for CSI corresponding to minimum TA5, the PDF shifts toward higher values for HistoricalExt simulations relative to HistoricalNatExt simulations, with a RR of $-10.0$ (90% CI 2.9–18.4) (Fig. 2d), indicating that strong cold events, like the one that occurred in April 2020, need stronger circulation under the influence of anthropogenic forcings relative to HistoricalNatExt simulations.

The human influences on monthly (16 April–15 May) mean temperature over Northeast China and the 500-hPa circulation strength have also been examined. Clearly, the average value of monthly mean temperature for HistoricalExt simulations is warmer than the counterparts for HistoricalNatExt simulations (Fig. 2e). Meanwhile, the monthly mean CSI shows insignificant changes under anthropogenic forcings (Fig. 2f). This further demonstrates that the anthropogenic forcings have substantially increased the mean state of temperature in late spring, which is attributed to the decline in the likelihood of the April 2020–like cold extremes.

Conclusions.

An exceptional spring cold event in 2020 swept across Northeast China and caused tremendous damage to agricultural production. Using the HadGEM3-GA6-based attribution system, we found that anthropogenic forcings have reduced the probability of April 2020–like cold spells over Northeast China by ~80%, in line with previous studies on spring cold events (Christidis and Stott 2020; Duan et al. 2021). The decline is mainly attributed to the substan-
tional increase of mean temperature induced by human influences, reconfirming the conclusions of Lu et al. (2020) and Sun et al. (2020). It is worth noting that such cold events tend to be triggered by more drastic dynamical factors to offset the anthropogenic warming, although the monthly mean circulation changes little.

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Anthropogenic Influences on 2020 Extreme Dry–Wet Contrast over South China

Jizeng Du, Kaiqi Fu, Kaicun Wang, and Baoshan Cui

The extreme precipitation and heatwave led to a 1-in-183-year extreme dry–wet contrast over South China in the 2020 summer. Anthropogenic influences increased the risk of such extremes by at least 3 times.

In the 2020 summer, the Yangtze River Basin (YZ) suffered catastrophic floods due to record-breaking precipitation. The floods affected more than 23.86 million people and 2,478 million hectares of crops, resulting in a direct economic loss of 10 billion dollars. However, near YZ, China’s southern coastal regions (SC) experienced a long-time heatwave, and the number of high temperature days was the second highest since 1961. In addition, the number of typhoons landing in South China was very low compared to recent years. There was a “no-typhoon July” for the first time since 1949 in SC. The low precipitation caused by the reduced number of typhoons, together with the continuous high temperature, resulted in the severe and persistent meteorological drought in SC (Liu 2021). Two opposite meteorological disasters occurred in two adjacent areas of South China.

With the occurrence of the El Niño event since autumn 2019, the SST over the northern Indian Ocean had been abnormally warm since April 2020, resulting in an intensified, westward, and larger area of the western Pacific subtropical high (WPSH) (Takaya et al. 2020; Zhou et al. 2021). Consequently, most of the SC region was controlled by the strong WPSH and thus had less...
cloud and precipitation, promoting high-temperature days (Choi and Kim 2019; Wang et al. 2013). The intensified subtropical high had dramatically inhibited the convective activities in the western tropical Pacific, making the region lack the necessary conditions for generating typhoons, resulting in fewer typhoons generating and landing at SC (Qi 2021). Additionally, the southwesterly wind west of the intensified WPSH transported more water vapor to the YZ (Zhou and Yu 2005). Then, it met with the abnormally active cold and dry air transferred by the northerly wind west of the Mongolian cyclone and formed a persistent and intense rainband in the YZ (Hsu and Lin 2007; Li et al. 2019). The rainband was mainly located in the middle and lower reaches of the YZ in July and gradually moved to the upper reaches in August, leading to frequent extreme precipitation in Guizhou, Chongqing, and Sichuan (Wei et al. 2020; Xia and Chen 2021).

The above anomalous circulations are closely related to both atmosphere internal variabilities and anthropogenic climate warming (Chen et al. 2021; Ding et al. 2020; Li et al. 2018; Liu et al. 2020; Zhou et al. 2021). Chen and Zhai (2017) suggested that the boreal summer intraseasonal oscillation (BSISO) can simultaneously facilitate precipitation extremes in central-eastern China and extreme high temperatures in South China and Southeast China. Additionally, Ye and Qian (2021) suggested that anthropogenic climate warming explains 80% and 99% of increasing risk for the record-breaking precipitation in YZ and the concurrent extreme heatwave in SC, respectively. Therefore, anthropogenic forcings may be an essential driving factor for the 2020 extreme dry–wet difference in South China.

Here, we used the Standardized Precipitation Evapotranspiration Index (SPEI) to measure the moisture conditions and answer the following two questions: 1) how extreme is the dry–wet contrast between YZ and SC and which is the key driving factor based on observations, and 2) whether and to what extent have anthropogenic influences amplified the risk of this extreme event based on model simulations. The exploration of extreme dry–wet contrast in South China is helpful to understand the risk from spatiotemporal compounding of multiple events.

Data and methods.

The daily observations from meteorological stations were provided by China’s Daily Dataset of Surface Climatic Data (V3.0). Totals of 133 and 114 meteorological stations were selected for YZ and SC from 1960 to 2020, respectively (see Fig. S1 in the online supplemental material). All observations have passed strict quality control and homogenization (Cao et al. 2016). Additionally, we used the model simulations for phase 6 of the Coupled Model Intercomparison Project (CMIP6) and the HadGEM3-A attribution system (HadGEM3-A) to assess the anthropogenic influences on the risk of extreme dry–wet contrast in South China.

As mentioned above, the extreme dry–wet contrast in South China was caused by simultaneous extreme precipitation and heatwave conditions. Therefore, we should select an index considering both precipitation and temperature to measure dry/wet condition variability. The SPEI index combines precipitation and air temperature and is commonly used to measure dry or wet conditions in previous studies (Beguería et al. 2014; Chiang et al. 2021; Vicente-Serrano et al. 2010). We produced the SPEI by the monthly precipitation from station observations and potential evapotranspiration (PET) calculated by the Thornthwaite equation (Stagge et al. 2014; Thornthwaite 1948; Zarei and Mahmoudi 2020). Positive and negative SPEI values correspond to relatively wet and dry conditions, respectively. Owing to the uneven distribution of weather stations across study regions, we divided all weather stations into the 1° × 1° grids. We first calculated the SPEI time series of every station and then calculated the area-weighted average of SPEI as regional means.

We used the difference of SPEI between YZ and SC (SPEI_D) to indicate the dry–wet contrast in South China. SPEI_D is the two-month moving average of SPEI_D and the persistent dry–wet
contrast event is defined as the maximum SPEI$_{Dx}$ in each year (hereafter SPEI$_{2Dx}$). After calculating the time series of SPEI$_{ip}$, we applied the Kolmogorov–Smirnov test to determine whether the probability density functions (PDFs) of simulated SPEI$_{ip}$ have the statistical significance of difference with the observed SPEI$_{ip}$ (Marsaglia et al. 2003). Then, we only kept model simulations whose PDFs of SPEI$_{ip}$ were indistinguishable from those from observations. Finally, we selected 24 simulations from six models for CMIP6 (Gillett et al. 2016) and 15 simulations for the HadGEM3A attribution system (Christidis et al. 2013) (see Table S1).

Table 1. The trends ($\pm$95% confidence level) of regional area-weighted average of precipitation ($P$) and air temperature ($T$) for Yangtze River Basin (YZ), China’s southern coastal regions (SC), and regional difference (YZ – SC) during 1960–2020. Bold font indicates the trend is significant at 95% confidence level.

<table>
<thead>
<tr>
<th>Variables</th>
<th>YZ</th>
<th>SC</th>
<th>YZ-SC</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P$ (mm/10 yr)</td>
<td>0.108 ± 0.243</td>
<td>0.006 ± 0.325</td>
<td>0.102 ± 0.191</td>
</tr>
<tr>
<td>$T$ (°C/10 yr)</td>
<td>0.020 ± 0.012</td>
<td>0.017 ± 0.015</td>
<td>0.003 ± 0.004</td>
</tr>
<tr>
<td>SPEI (10 yr)</td>
<td>0.0001 ± 0.0018</td>
<td>-0.0042 ± 0.0021</td>
<td>0.0041 ± 0.0025</td>
</tr>
</tbody>
</table>

We applied the generalized extreme value (GEV) model to fit the distribution of SPEI$_{2Dx}$ from observations or simulations to estimate the probability and return period for the extreme SPEI$_{2Dx}$ in varying scenarios (Huang et al. 2016; Jenkinson 1955). The variations of SPEI mainly involved both precipitation and air temperature. Here, we quantify the contribution of variables by calculating SPEI using original data and detrended data. If variable $i$ is the input variable to SPEI, we replaced the observed $i$ variable with its detrended time series. The detrended series has no long-term trend but this does not affect the original data distribution and interannual variabilities. Therefore, we can calculate the probability ratio (PR) and the fraction of attributable risk (FAR) for the $i$ variable as follows (Fischer and Knutti 2015; Stott et al. 2016):

$$PR(i) = P(i) / P(NTD) \text{ and } FAR(i) = 1 - P(NTD) / P(i),$$

where $P(NTD)$ indicates the probabilities of exceeding the 2020 extreme SPEI$_{2Dx}$ event threshold in the scenario that all input variables have been replaced by detrended data, and $P(i)$ indicates the probabilities exceeding such extremeness in the scenario where the $i$ variable has been replaced by observation. We used the NAT scenario to estimate $P(NTD)$ and the $i$ variable from ALL scenario to estimate $P(i)$ for model simulations. A Monte Carlo bootstrap procedure estimated the 2.5%–97.5% uncertainties of the above indicators.

Results.

Observed extreme dry–wet contrast. During July–August 2020, the total precipitation in YZ broke the historical record of half a century and reached 482.22 mm, significantly exceeding the previous record during 1960–2020 by 151.70 mm (see Fig. 1a). Conversely, the concurrent total precipitation in SC was 335.92 mm and 56.49 mm less than the historical average in 1960–2020. The concurrent air temperature in SC was 0.74°C higher than in average years (see Fig. 1b), and the extreme heat days reached 11.5 days, which is 2.6 days more than the historical average. In the same period, the frequent heavy rainfall and the high temperature with less precipitation had resulted in a severe flood in YZ and extreme drought in SC, respectively (see Fig. 1c).

As shown in Fig. 1d, the SPEI was positive in YZ but generally negative in SC during July–August 2020. The regional mean SPEI in YZ broke the historical highest record while that in SC was the third-lowest since 1960. Therefore, the SPEI$_{Dx}$ between YZ and SC reached the
The return period of the 2020 extreme SPEI2 Dx is a 1-in-183-yr event [the 95% confidence interval (CI) is 41–1361 yr; see Fig. 1e].

In the past 60 years, there were significant warming trends in both YZ and SC (see Table 1). The precipitation increased in YZ while remaining stable in SC. Hence, compared with the YZ region, SC showed a dry and warm trend. Additionally, the difference in extreme precipitation and heatwave between YZ and SC seem to be more sensitive to anthropogenic forcings.

As shown in Fig. S2, the increased rate of extreme precipitation (excess 90% quantile) was higher in YZ than SC while that of extreme high temperature (excess 90% quantile) was the
opposite. The above results may suggest that anthropogenic forcings facilitated more extreme precipitation in YZ and heatwave events in SC, thus further increasing the occurrence risk of extreme dry–wet contrast events between the two regions.

Model attribution. Here, we quantify the anthropogenic influences on extreme SPEI\(_2Dx\) event by comparing scenarios under all forcings (ALL) and natural forcings only (NAT) from HadGEM3A (Christidis et al. 2013; Ciavarella et al. 2018). ALL and NAT simulations during 1960–2015 are
freely available in NetCDF4 format from the Earth System Grid Federation Centre for Environmental Data Analysis (ESGF/CEDA; https://catalogue.ceda.ac.uk/). Note that the ALL scenarios are not stationary climates, and their mean during 1960–2015 is not representative of the climate state in 2020. Hence, the scaled GEV distributions are determined to fit the probability distribution of SPEI$_{3dx}$ in ALL scenarios (see the online supplemental material).

As shown in Figs. 2d and 2e, we found that the likelihood of the 2020 SPEI$_{3dx}$ anomaly of ALL was 3.51 times (95% CI: 2.01–12.58) that of NAT. Therefore, the anthropogenic effects can explain 71.5% (95% CI: 50.2%–92.1%) attributable risk of the extreme SPEI$_{3dx}$ experienced in July–August 2020 (see Figs. 2b–d).

Besides, we combined historical simulations (2000–14) and corresponding Shared Socioeconomic Pathway (SSP) 2–4.5 scenarios (2014–40) to construct the scenario with all forcings and the scenario with only natural forcings as reference. According to the CMIP6 experiments, the likelihood of the 2020 extreme SPEI$_{3dx}$ under ALL was 3.12 times (95% CI: 1.41–11.12) than under NAT (see Fig. 2d). Anthropogenic climate change explains 67.9% (95% CI: 29.1%–91.0%) of the attributable risk of 2020 extreme SPEI$_{3dx}$ (see Fig. 2f).

**Key driving factor.** As shown in Fig. 2b, precipitation variations are the most crucial driving factor leading to extreme SPEI$_{3dx}$ events among all the related meteorological variables. Compared with detrended data, the precipitation and temperature can increase the probability of extreme SPEI events by 3.48 times (95% CI: 2.07–13.21) and 2.05 times (95% CI: 1.03–7.14), respectively. The combined effect of the two increased the probability of extreme SPEI$_{3dx}$ by 4.58 times (95% CI: 2.51–15.27), explaining 78.2% of the attributable risk (see Fig. 2c). According to HadGEM3A and CMIP6, human-induced precipitation changes increased the risk of extreme SPEI$_{3dx}$ by 1.76 times (95% CI: 0.85–9.14) and 2.31 times (95% CI: 1.24–8.37) (see Figs. 2f, i). Hence, anthropogenic forcings significantly affect the precipitation difference but have less effect on the warming difference between YZ and SC. Therefore the extreme SPEI$_{3dx}$ risk was more sensitive to precipitation changes than regional warming.

**Conclusions.**

In the 2020 summer, an extreme dry–wet contrast occurred over South China due to frequent extreme rainfall in the Yangtze River Basin and persistent heat and drought in China’s southern coastal regions, breaking the historical record since 1960. Precipitation changes are the main reason for regional extreme dry–wet contrast over South China, followed by temperature variation, which increased the probability of the extreme event by 3.48 and 2.05 times, respectively.

Based on the simulation results of HadGEM3A (CMIP6), anthropogenic climate change increased the probability of the 2020 extreme SPEI$_{3dx}$ by 3.51 (3.12) times, which can explain the 71.5% (67.9%) attributable risk. Anthropogenic climate change increased the risk of extreme dry–wet contrast events mainly by altering precipitation. Precipitation and temperature changes have an apparent synergistic effect in increasing the risk of such extreme events. Additionally, based on CMIP6 simulation, Chiang et al. (2021) found that anthropogenic climate forcing, primarily anthropogenic aerosol emissions, significantly increase drought risk in South China. The increased intensity in China’s southern coastal regions is considerably higher than that in the Yangtze River Basin. Although we detected the effect of anthropogenic forcings on this extreme dry–wet contrast event, it is necessary to explore related physical processes in the future.

Note that Berg and Sheffield (2018) have criticized the use of SPEI for climate trend analysis and projections and particularly to infer soil moisture–related drought changes. They find an unrealistically strong temperature-driven response of SPEI to warming compared to soil moisture responses in model projections. However, we contrast the SPEI between two regions
with similar warming trends, and the differences in precipitation trends mainly drive the trend in SPEI difference between the regions. The issues with interpreting SPEI trends identified by Berg and Sheffield are less likely to have a large influence on our results compared to an analysis of SPEI trends for individual warming regions.

Acknowledgments. This study was funded by the National Basic Research Program of China (2018YFC1507701 and 2017YFA0603601), the Fundamental Research Funds for the Central Universities (2019NTST01), and the National Natural Science Foundation of China (42005019). We thank the Met Office for the HadGEM3-A-based attribution system (http://catalog.ceda.ac.uk/) and the World Climate Research Programme’s Working Group on Coupled Modeling (http://cmip.pcmdi.llnl.gov/cmip6/) for the model simulations.

References


Was the Record-Breaking Mei-yu of 2020 Enhanced by Regional Climate Change?

Yuanyuan Ma, Zhiyuan Hu, Xianhong Meng, Fei Liu, and Wenjie Dong

In 2020, the middle and lower reaches of the Yangtze River (MLYR; 28°–33°N, 110°–121°E) in China suffered an unexpected long-persisting mei-yu season, and both the duration and rainfall amount reached the highest record since 1961 (Wei et al. 2020). In particular, the average cumulative precipitation for the period of 1 June to 31 July exceeded +750 mm with a maximum value of 1720 mm, and the precipitation anomaly reached +350 mm (Fig. 1a), which was about 88% more than 1980–2010 climatology in this region (Fig. 1b). The corresponding extreme precipitation caused severe flooding over the MLYR region, affecting 63.46 million people and resulting in a direct economic loss of over 178.96 billion Yuan (https://www.chinanews.com/sh/2020/08-14/9264482.shtml).

This super mei-yu was primarily driven by the enhanced upward movement and moisture flux (Fig. 1c). They were caused by the abnormal East Asian westerly jet in the upper level and the southwesterly jet in the lower level, which were associated with abnormal position and intensity of the western Pacific subtropical high (Ding et al. 2021). These circulation anomalies coincided with the North Atlantic Oscillation (NAO; Liu et al. 2020), North Atlantic SST anomaly (Zheng and Wang 2021), the strong preceding Indian Ocean dipole (IOD; Takaya et al. 2020; Z.-Q. Zhou et al. 2021), a rap-
Fig. 1. (a) The observed rainfall anomalies relative to 1981–2010 climatology. The black box denotes the MLYR region (28°–33°N, 110°–121°E). (b) Time series of accumulated rainfall percentage anomalies for the black box in (a) during 1 Jun to 31 Jul relative to 1981–2010. (c) 500-hPa vertical velocity anomalies (shading; 10^{-2} Pa s^{-1}; negative values denote upward motion) and 850-hPa moisture flux anomalies (vectors; g m^{-1} s^{-1} Pa^{-1}) during 1 Jun to 31 Jul relative to 1981–2010. (d) Model domains and trend of 2-m temperature during 1980–2020, where the dotted area is the region exceeding the 95% confidence level. (e) Vertical profiles of regional-mean air temperature (Tem) and specific humidity (SH) trend over the model domain, where the 95% confident level of area-average field are marked with a plus sign (+).
idly developing La Niña (Z.-Q. Zhou et al. 2021), and an exceptionally persistent MJO active phase in the Indian Ocean (Zhang et al. 2021). Besides, the air temperature in Asia has been increasing rapidly (e.g., Huang et al. 2012; Kawase et al. 2020) and it is possible that climate change contributed to the extreme rainfall in 2020.

When attributing a specific extreme event to climate change, the approaches are important to extend the chain of complex physical causality. Generally, an “absolute” approach assesses overall changes in event likelihood, but the contribution of specific aspect of climate change is not considered (Swain et al. 2020). The “ingredient-based” approach with both absolute and conditional frameworks can ascertain the most essential physical conditions and then assess changes in the probability of these conditions (Swain et al. 2020). The “storyline” approach (Shepherd et al. 2018) typically uses a regional model to simulate an observed event under different boundary forcing and can offer better understanding of local-scale processes such as thermodynamical and dynamical changes (Meredith et al. 2015a,b). In this study, we will apply the storyline approach to evaluate the impact of climate change on the extreme rainfall event on a physically based causal narrative.

Data and methods.

The gauge observations of daily precipitation during 1961–2020, using ~824 stations over China with rigorous quality control (Cao et al. 2016), are obtained from the China Meteorological Administration to examine this mei-yu event from the perspective of climate. The quasi-real-time hourly precipitation data collected from ~2400 stations, with quality control performed for the hourly precipitation from the Chinese hourly gauge network (Shen et al. 2010), are used to validate the simulated precipitation.

We investigate the impact of post-1980 regional climate change on the super-mei-yu using the Weather Research and Forecasting (WRF) model. The initial conditions and boundary meteorological fields (IBCs) are obtained from the National Centers for Environmental Prediction final analysis (NCEP/FNL) data with 1° horizontal resolution and 6-h temporal intervals. The model domain centers at 30°N, 105°E with grid numbers of 280 × 220 and spacings of 27 km (Fig. 1d). The unevenly spaced terrain-following vertical coordinate levels are used with 38 vertical layers up to 50 hPa. To better capture this mei-yu rainfall, a series of parameterization schemes are tested and the final main physical options are listed in Fig. S1b in the online supplemental material.

Two series of ensemble simulations are carried out to assess the sensitivity of the extreme mei-yu rainfall to regional climate change. One ensemble of simulations is driven with realistic IBCs based on the NCEP/FNL data (CTL runs), and the other has the identical setup, except that trend of the post-1980 regional climate change estimated by the fifth generation European Centre for Medium-Range Weather Forecasts atmospheric reanalysis data is removed from the IBCs. The method of subtracting the climate change trend is usually used to evaluate the impact of climate change by the “storyline” approach (Swain et al. 2020). It has been useful for extreme rain events in the United States (e.g., Wang et al. 2018), Japan (e.g., Kawase et al. 2020), India (e.g., Cho et al. 2016), and over the Black Sea and Mediterranean region (e.g., Meredith et al. 2015a,b). Note that the trend in climate change includes both anthropogenic global warming and natural decadal variability, but the atmosphere warming and moistening in Asia can be largely attributed to human activities (Zhang et al. 2019). Based on the adjusted variables, six sensitivity experiments, including the Dair, Dair_TQH, Dair_TH, Dair_Q, and Dair_UV runs, are set and more information can be found in Fig. S1b. All simulations are conducted from 25 May to 1 August 2020, and the days before 1 June are considered as a spin-up period (Zhong et al. 2007; Jerez et al. 2020).
Fig. 2. (a) Gauge-analyzed total precipitation from 1 Jun to 31 Jul 2020. (b) As in (a), but for the ensemble means of precipitation from CTL runs. (c) Time series of regional-averaged daily (bar) and accumulated precipitation (line) over the MLYR region. (d) The minimum, maximum, and mean total precipitation and the standard deviations simulated by each experiment. The x-axis labels marked with an asterisk (*) indicate a significant difference from CTL runs at 95% confidence interval by a t test. (e) Difference of total precipitation (shading, mm) and 850-hPa moisture flux (vectors; g m$^{-1}$ s$^{-1}$ Pa$^{-1}$) between the CTL runs and Dair runs. (f) Vertical profiles of regional-mean vertical velocity of CTL runs (m s$^{-1}$) and the difference in the vertical velocity (10$^{-1}$ m s$^{-1}$) compared with CTL runs.
This study aims to conduct several months of regional climate simulation to evaluate the effects of climate change on the long-persisting mei-yu season of 2020. To reduce and assess the uncertainties, each experiment adopts a piecewise-integration method (Zhang et al. 2008) and has six ensemble runs with different microphysical parameterizations (see Fig. S1b). This setup gives a high signal-to-noise ratio, which allowing fewer members and better understanding of thermodynamical and dynamical responses of climate change (Meredith et al. 2015a,b). Experiments with realistic IBCs show that the piecewise-integration method can effectively reduce simulated precipitation biases compared with the continuous-integration method (Figs. S1c,d).

Results.

The climate in Asia became warmer and more humid from 1980 to 2020 (Fig. 1d and Fig. S1a). During this time, the temperature increases are most apparent in mid- and high-latitude regions, while specific humidity increases are clearest over the ocean. The climate warms most in the lower and upper atmosphere and humidity increases are greatest in the middle atmosphere (Fig. 1e).

The ensemble mean of six CTL runs reasonably captures the intensity and location of the accumulated precipitation amount during the extreme rainfall event (Figs. 2a,b). Also, the CTL runs well reproduces the cumulative process of precipitation of the heavy rainfall event (Fig. 2c). Specifically, the simulated regional-mean total precipitation amount is 777.9 mm with a standard deviation of 17.3 mm and a high signal-to-noise ratio of 45.0. Compared with observations, the total precipitation bias is 31.6 mm, which only accounts for approximately 4.2% of observed precipitation.

The difference in the total precipitation between the ensemble mean of CTL runs and Dair runs shows that post-1980 climate change decreases precipitation over the MLYR (Fig. 2e). Comparing the timing evolution of the accumulated precipitation between CTL runs and Dair runs, we can see that the difference in ensemble mean precipitation starts at 1 June and increases gradually to the end of the heavy precipitation event (Fig. 2c). The difference is –107.7 mm at 31 July (Fig. 2d), which is equivalent to –11.9% (–14.1% to –9.2%) relative to the Dair runs (Fig. S2a). Further, the influence of climate change on this extreme event mainly occurs through the temperature and geopotential, while the effects of relative humidity and horizontal winds are very small (Fig. 2d).

To understand the pronounced changes in precipitation, we further address the relative roles of thermal and dynamical changes induced by the climate change. Comparatively, the equivalent potential temperature (Fig. S2c) and the water vapor mixing ratio (Fig. S2d) are increasing significantly in the lower and middle atmosphere, but decreasing in the upper atmosphere, indicating the enhanced atmospheric thermal instability and humidity in the CTL runs. However, these local thermal changes do not induce increased precipitation, probably because of the maximum warming and moistening at ~850 hPa, which cause more stable stratification conditions in the lower atmosphere. Dynamical changes show that the climate change induces northeast–southwest direction moisture flux and wind field anomaly and a strong downward movement (Fig. 2e and Fig. S2b), which is opposite to the circulation anomalies of East Asian summer monsoon (EASM) circulation (Fig. 1c). The differences in vertical velocity profiles show a clear weakened upward movement in the CTL runs and the change of vertical movement is consistent with the change of precipitation (Fig. 2f). This demonstrates that the climate change decreases the precipitation mainly by the circulation anomalies related to dynamical changes, which indicates the weakened large-scale background EASM circulations. The weakening EASM may be associated with the increased static stability in the vertical atmosphere (Held and Soden 2006; Liu et al. 2013), land–sea thermal contrast (Kamae et al. 2014), and spatial inconsistency of global warming (Zuo et al. 2012).
Conclusions.
This study evaluates the contribution of regional climate change to the super-2020 mei-yu rainfall event over the MLYR region by a “storyline” approach. The model reasonably captures the spatial distribution and cumulative process of total precipitation amount. Sensitivity experiments indicate that the post-1980 regional climate change in IBCs reduces the total precipitation by approximately 9.2%–14.1%. The weakened precipitation is mainly attributed to the EASM circulation anomalies associated with dynamical changes. This is consistent with T. Zhou et al. (2021), who showed that anthropogenic forcing reduced the probability of the 2020 extreme rainfall through weakening the EASM circulation caused by anthropogenic aerosols. Therefore, precipitation changes in China are related not only to changes in atmospheric temperature and moisture, but also to changes in the background atmosphere circulations. This study demonstrates that regional climate change in Asia is unfavorable for this rainfall event, and thus extreme external forcings, such as the IOD, NAO, and El Niño–Southern Oscillation (ENSO), on such events may play the dominant roles (e.g., Ding et al. 2021; Z.-Q. Zhou et al. 2021; Liu et al. 2020). Future work is required to evaluate the influence of global warming or climate change in specific external forcings (e.g., ENSO and IOD) on the 2020 rainfall event.

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References


Reduced Probability of 2020 June–July Persistent Heavy Mei-yu Rainfall Event in the Middle to Lower Reaches of the Yangtze River Basin under Anthropogenic Forcing


Anthropogenic forcing has approximately halved the probability of 2020 June–July persistent heavy mei-yu rainfall event based on HadGEM3-GA6 simulations without considering the COVID-induced aerosol emission reduction.

During June–July (JJ) 2020, the mid-lower reaches of the Yangtze River basin (MLYRB; gray shading in Fig. 1a) in China witnessed a persistent heavy rainfall event (herein simply referred to as the 2020 mei-yu event). The total accumulated rainfall over the MLYRB during the period from 11 June to 15 July in 2020 was 87% above the 1981–2010 climatology. With the largest total rainfall amount (759.2 mm) and the longest duration (62 days) of the mei-yu season since 1961, this persistent heavy rainfall event threatened ~45.5 million people, with 142 people missing or dead and 29,000 homes destroyed, causing a direct economic loss about 16 billion U.S. dollars (CMA 2021; Wei et al. 2020).

Thus, local inhabitants and policymakers are eager to know whether human-induced climate change played a role in the 2020 mei-yu event and, if so, to what extent and through what mechanisms. Such knowledge will enable practical ad-
Fig. 1. (a) Observed accumulated precipitation (AP) anomalies (mm) during JJ 2020, with inset showing the daily rainfall evolution of which dashed green line for the mean value, green curve for 7-day running average, and blue dots for the daily climatology. (b) Time series of regional mean Rx28day% for observations (bar) and Historical simulations (red line and pink shading). (c) Return periods of observed Rx28day% in GEV fit with 90% uncertainty range, with a red star for the 2020 event and blue circles for other years. (d) Anomalies of SLP (shading; Pa) and column-integrated water vapor flux (vectors; kg m\(^{-1}\) s\(^{-1}\)) during JJ 2020. The MLYRB is highlighted in red. (e) PDFs of Rx28day% for observations (blue) and Historical simulations (red) with p value for the K-S test.
adaptation and mitigation planning. Therefore, this study aims to assess the contribution of anthropogenic forcing on the likelihood of the 2020 mei-yu event using the HadGEM3-GA6 attribution system (Ciavarella et al. 2018).

Data and methods.
Gauge-based daily rainfall observations from 2419 meteorological stations in China for 1961–2020 with strict quality control (http://data.cma.cn/) are used in this study. The data are gridded to a horizontal resolution of $1^\circ \times 1^\circ$ by averaging all stations over each grid cell that contains at least one station. Monthly horizontal winds, specific humidity, and sea level pressures (SLP) from the NCEP–NCAR reanalysis (Kalnay et al. 1996) and sea surface temperature (SST) from the Hadley Centre (Rayner et al. 2003) are also used.

The HadGEM3-GA6 model simulations with horizontal grid spacings of $0.56^\circ \times 0.83^\circ$ (Ciavarella et al. 2018) are employed to conduct this attribution analysis. Model simulations are locally area averaged into the $1^\circ \times 1^\circ$ grid as in observations. Five sets of simulations [see details in Christidis et al. (2013)] are used:

1) the Historical ensemble, comprising 15 initial-condition simulation members for 1960–2013, driven by observed SST and sea ice concentration (SIC) with anthropogenic (including anthropogenic aerosols, greenhouse gases, and land use and land cover changes) plus natural (volcanic aerosols and solar irradiance) forcings;

2) the HistoricalExt ensemble, which is similar to the Historical ensemble but with 525 members and driven by 2020 SST and SIC boundary conditions;

3) the HistoricalNatExt ensemble, which differs from HistoricalExt experiment by including only natural forcings and with the 2020 SST and SIC having human influences removed; and

4) HistoricalExt and 5) HistoricalNatExt ensembles for 2019, which are used to compare the results with those for 2020.

Rx28day is defined as the seasonal maxima of consecutive 28-day total regional-mean rainfall over the MLYRB in June–August and used to measure both the intensity and duration of the 2020 mei-yu event. Anomalous Rx28day is calculated and expressed as a percentage of the 1981–2010 mean (termed Rx28day%; Hoerling et al. 2013), which provides a simple correction of model biases (see Figs. ES1a,b in the online supplemental material; Zhang et al. 2020). The accumulated precipitation (AP) averaged over the MLYRB from 20 June to 12 July is also calculated, given that the 2020 mei-yu rainfall was the heaviest during this period (Fig. 1a). The AP index is also transformed into AP%.

The probability density function (PDF) is estimated by the generalized extreme value (GEV) distribution for both the simulations and observations. The two-sample Kolmogorov–Smirnov (K-S) test, probability ratio ($PR = P_{\text{ALL}} / P_{\text{NAT}}$) and the uncertainty in PR (estimated via bootstrapping; Efron and Tibshirani 1994) are also used. The terms $P_{\text{ALL}}$ and $P_{\text{NAT}}$ are the occurrence probability of events exceeding the 2020 mei-yu event threshold in the GEV-fitted HistoricalExt and HistoricalNatExt ensembles, respectively.

Results.
Figure 1a illustrates the spatiotemporal characteristics of the 2020 mei-yu event. The observed Rx28day is about 60% above the 1981–2010 climatology, surpassing two standard deviations and being about a 1-in-60-year event in the 1960–2020 observations (Fig. 1b). The results are similar when the long-term trend is removed (Fig. 1b). The 2020 mei-yu event is possibly associated with the intensification and westward shift of the western Pacific subtropical high
increased by about 28% in the MLYRB (Fig. 1b). However, it should be mentioned that the interannual variability of RX28day% is still hard to be well simulated considering the multiscale feedback processes inherent in the Asian monsoon system. The PDFs of the Rx28day% are similar between model simulations and observations, since they cannot be distinguished at the 0.05 significance level (Fig. 1e). Taken overall, the model can be regarded as reliable for the attribution of 2020 mei-yu event.

The PDFs of Rx28day% show a clear drying shift from 2020 HistoricalNatExt to HistoricalExt simulations, indicating that rainfall similar to or heavier than that of the 2020 mei-yu event occurs less frequently due to human-induced climate change (Fig. 2a) and corresponding to increased return periods from HistoricalNatExt (1 in 31 years) to HistoricalExt (1 in 55 years). Anthropogenic forcing has reduced the occurrence probability of the 2020 mei-yu event from 0.033 (0.023–0.042) for $P_{\text{nat}}$ to 0.018 (0.013–0.024) for $P_{\text{ALL}}$, giving a PR of 0.56 (0.36–0.87). This indicates that anthropogenic forcing has approximately halved the probability of 2020 mei-yu event, consistent with the results based on 10 models from phase 6 of the Coupled Model Intercomparison Project (CMIP6) in T. Zhou et al. (2021). Similar analysis using AP% gives a PR of 0.63 (0.47–0.93), confirming the robustness of the attribution results (Figs. ES2a,f). These conclusions also hold for a rectangular region (27°–34°N, 105°–121°E; Figs. ES2a,d; Liu et al. 2020) and when the boundaries are adjusted slightly (Figs. ES2a–c,e).

To understand the reduced probability of the 2020 mei-yu event due to anthropogenic forcing, atmospheric circulation differences are analyzed. The East Asian summer monsoon (EASM) index is defined as anomalous SLP difference between $5^\circ$–$15^\circ$N, $90^\circ$–$130^\circ$E and $22.5^\circ$–$32.5^\circ$N, $110^\circ$–$140^\circ$E where a positive index means stronger southwesterlies over East Asia. The negative shift of EASM index from 2020 HistoricalNatExt to HistoricalExt simulations shows that anthropogenic forcing leads to a weakening EASM (Fig. 2b). The differences in JJ mean rainfall and SLP between 2020 HistoricalNatExt and HistoricalExt simulations further show reduced JJ mean rainfall and increased SLP over large areas of East Asia from anthropogenic forcings (Fig. 2c). Further disentangling the weakened EASM suggests that the weakening effect of anthropogenic aerosols on EASM may overwhelm the boosting effect of greenhouse gases, leading to a net effect of reduced probability for 2020 mei-yu event under anthropogenic forcing (e.g., Lau 2016; Lau and Kim 2017; Dong et al. 2019; T. Zhou et al. 2021). It is also worth noting that the present-day situations do not indicate the future changes since similar persistent heavy rainfall events are projected to occur more frequently with continuous emissions of greenhouse gas and reductions in aerosols (T. Zhou et al. 2021).

The potential role of year-to-year boundary conditions (SST/SIC) on the risk of the 2020 mei-yu event is next investigated. Since anthropogenic forcing of 2019 and 2020 HistoricalExt simulations are taken from CMIP5 model forcings, the difference between them is negligible. Thus, the primary factor leading to the shift of Rx28day% PDFs (Fig. 2a) are different time evolutions of SST/SIC during two years. The 2020 HistoricalExt PDFs shift toward larger rainfall anomalies compared to those of 2019 (Fig. 2a). Thus, the 2020 mei-yu event is more likely to occur with the time evolutions of SST/SIC in 2020 than those in 2019, with the likelihood increased by about 3 (a possible range of 1.7–8.6) times. PR, relative to HistoricalNatExt, increases from 0.21 (0.08–0.45) in 2019 to 0.56 (0.36–0.87) in 2020, implying a nonlinear impact of boundary conditions in this climate versus weather blame game (King et al. 2016; Zhou et al. 2018).

As for possible reasons for changing PR between 2019 and 2020, Takaya et al. (2020) and Z.-Q. Zhou et al. (2021) suggested the positive Indian Ocean Basin mode (IOBM) in the 2020 El Niño decaying summer (Fig. 2e) evolving from positive Indian Ocean dipole in 2019 (Fig. 2f) as
Fig. 2. (a) The PDFs of Rx28day% for HistoricalExt (red) and HistoricalNatExt (blue) simulations in 2019 (dashed) and 2020 (solid). The dotted black line denotes the observed 2020 event. (b) The PDF of 2020 EASM index, calculated by JJ mean anomalous SLP difference (Pa) between blue and green box [(e) and (f)] for 2020 HistoricalExt (red) and HistoricalNatExt (blue) simulations. (c) Ensemble mean differences of JJ mean precipitation (shading; mm day$^{-1}$) and SLP (contours; Pa) between 2020 HistoricalExt and HistoricalNatExt simulations. Dots denote the region with 5% significance level, and MLYRB is highlighted in red. (d) As in (c), but for differences between 2020 and 2019 HistoricalExt simulations. Also shown are the (e) 2020 and (f) 2019 JJ mean SST anomalies (°C) relative to the climatology of 1981–2010.
the mechanism, which intensified the WPSH through atmospheric wave responses. The central Pacific El Niño in the 2019 El Niño developing summer (Fig. 2f) is not in favor of the simultaneous rainfall in the MLYRB (Xu et al. 2020). Enhanced WPSH and rainfall at its northern flank from 2019 to 2020 HistoricalExt simulations (Fig. 2d) further suggest that different time evolutions of SST/SIC during two years may modulate atmospheric circulation and therefore the PR of the 2020 mei-yu event between 2019 and 2020. Besides, it is worth mentioning that natural variability like El Niño may be modulated in frequency and intensity by anthropogenic forcing (e.g., Yeh et al. 2018; Hu et al. 2021). Therefore, the nonlinear feedback between “natural variability” and “anthropogenic forced” changes cannot be neglected.

Conclusions.
Through comparison between 2020 HistoricalNatExt and HistoricalExt ensembles, this study suggests that anthropogenic forcing has approximately halved the probability (13%–64%) of the 2020 mei-yu event in the MLYRB, likely related to a weaker EASM arising from anthropogenic (probably aerosol) forcings (Dong et al. 2019). The attribution results are robust against different extreme rainfall indices or small changes to the study region. Through comparison between the 2019 and 2020 HistoricalExt ensembles, this study further indicates that the time evolutions of SST/SIC in 2020 increased the likelihood of the 2020 mei-yu event by about 3 (1.7–8.6) times compared to 2019. One caveat of this study is that model simulations do not consider the COVID-induced aerosol emission reduction in 2020, which is speculated to enhance the Asian summer monsoon (e.g., Fadnavis et al. 2021). The extent to which COVID-19 may have influenced the 2020 mei-yu event still needs future detailed numerical experiments.

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References


Human Contribution to the 2020 Summer Successive Hot-Wet Extremes in South Korea

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Greenhouse gas forcing has significantly increased the risk for successive hot-wet extremes as observed over South Korea in summer 2020, through intensifying hot extremes while hardly affecting wet extremes.

During the summer 2020, South Korea was struck by successive hot-wet extremes. A strong heat wave occurred during June, resulting in the highest June temperature since 1973 with a significant impact on society. The station-averaged temperature (June $T_{mean}$) was 1.60°C warmer (57-yr return value based on Gaussian fitting) than the 1981–2010 climatology (Fig. 1a). This heat wave was characterized by a westward extended anticyclonic circulation anomaly in the midtroposphere over the Korean Peninsula (Fig. 1c). From early July to mid-August, there was an extremely long wet period with the largest number of heavy rain events on record (KMA 2021), which brought deadly floods and landslides at many places, causing tremendous property and infrastructure damages (0.8 billion U.S. dollars) as well as 46 deaths (KMA 2021). When using an index for heavy precipitation frequency ($R_{50}$ mm; defined as the station-averaged number of days with daily precipitation ≥ 50 mm), the 2020 July–August (JA)
Fig. 1. (a) Observed time series of South Korean averaged June $T_{\text{mean}}$ anomalies over 1973–2020 and model-simulated ranges of normalized June $T_{\text{mean}}$ from CMIP6 (ALL, GHG, NAT, and AER) and HadGEM3-A-N216 (ALL and NAT). (b) As in (a), but for JA R50mm. Anomaly distributions of (c) 2020 June $T_{\text{mean}}$ (shading) and 500-hPa geopotential height ($H_{500}$; contour) obtained from ERA5 reanalysis and (d) 2020 JA mean precipitation (PR; shading) from GPCP and $H_{500}$ from ERA5 reanalysis. The light and dark green lines represent 5880-gpm contours observed in 2020 and its climatology (1981–2010), respectively. All anomalies are relative to 1981–2010 means.
R50mm was 5.5 days (22-yr return value based on lognormal fitting, Fig. 1b), the second highest after 1987. In JA, cold air around the Korean Peninsula and the westward expansion of the North Pacific high induced a frequent development of midlatitude cyclones and a quasi-stationary front around South Korea, resulting in long-lasting rainfall (Fig. 1d; Park et al. 2021). Given no significant correlation between June $T_{\text{mean}}$ and JA R50mm in the historical record, this successive hot-wet extreme event has likely occurred just by chance. In spite of their rarity, compound (co-occurring) and cascading events exert stronger socioeconomic impacts than individual events (Leonard et al. 2014; Zscheischler et al. 2018; AghaKouchak et al. 2020; Kemter et al. 2021), and usually have a physical basis for being linked like hot droughts (e.g., Cheng et al. 2019). However, limited studies have assessed human influences on successive extreme events occurring without obvious physical interactions such as the 2020 hot-wet events in South Korea. These events can be a new hazard for society although mutual reinforcement or conditional dependency between them remain unclear.

This study investigates anthropogenic and natural contributions to the 2020 summer successive hot-wet extremes in South Korea using the Coupled Model Intercomparison Project phase 6 (CMIP6) multimodel simulations and HadGEM3-A large-ensemble simulations. Univariate and joint probabilities of occurrence of a June heat wave, and JA frequent heavy precipitation events are compared between real and counterfactual world experiments.

Data and methods.

Daily mean temperature and precipitation from 45 South Korean weather stations are used as observations for 1973–2020 (Fig. S1 in the online supplemental material), for which data quality and homogeneity have been checked (KMA 2016; Park and Min 2017). We take station averages to obtain South Korean mean values for June $T_{\text{mean}}$ and JA R50mm. R50mm is selected to better capture consecutive heavy rain events, compared to total precipitation or $n$-day accumulated precipitation (cf. Park et al. 2016; Guo and Huang 2016).

Multimodel datasets from CMIP6 (Eyring et al. 2016) are used, which include historical (natural plus all anthropogenic, called ALL), greenhouse-only (GHG), natural-only (NAT), and aerosol-only forcing (AER) simulations from 11 models with a total of 37 ensemble members (see Table S1 in the online supplemental material). To cover the 2020 summer, historical simulations (2001–14) are combined with corresponding Shared Socioeconomic Pathway (SSP) 2–4.5 scenarios (2015–20). The data over the recent 20 years (2001–20) are then used as samples representing the year 2020 conditions. This gives 740 samples (20 years × 37 ensemble members) for different forcing scenarios.

HadGEM3-A large-ensemble simulations performed for 2020 provide 525 members for ALL and NAT each on a resolution of 0.83° × 0.56° (HadGEM3-A-N216; Ciavarella et al. 2018; Vautard et al. 2019). The real world simulations (ALL) were carried out by prescribing the 2020 observed sea surface temperature (SST) and sea ice concentration (SIC) from HadISST1 (Rayner et al. 2003) and also by implementing the observed greenhouse gas and aerosol forcings. The counterfactual world simulations (NAT) were performed by using adjusted observed SST and SIC with their anthropogenic changes removed and setting other external forcings as pre-industrial levels. Here the anthropogenic changes (i.e., delta-SST) are estimated from 19 CMIP5 models (as ALL-NAT; Stone and Pall 2020).

Model climatology (1981–2010) is defined as each model’s ensemble mean of ALL simulations (Table S1). To account for model biases in temperature variability, observed and simulated June $T_{\text{mean}}$ anomalies are normalized with respect to mean and interannual standard deviation of each dataset for the climatology period. The GHG, NAT, and AER runs are normalized based on ALL climatology of each model. To account for model biases in daily precipitation distribution, we apply a different threshold for heavy precipitation to each model, which is equivalent to the observed R50mm (Table S1). The probability of JA R50mm higher than that
observed in 2020 is 3.33% during 1981–2010 (i.e., the 2020 case is a 1-in-30-yr event) and we find each model’s heavy rainfall threshold using ALL simulations for 1981–2010, which corresponds to the same 30-yr return value of daily precipitation. A composite analysis (Fig. S2) indicates that CMIP6 and HadGEM3-A simulations can largely capture the observed circulation patterns associated with hot-wet extremes (Figs. 1c, d), including the anomalous high over the Korean Peninsula in June and the westward extended subtropical high in JA.

The risk ratio (RR) is mainly analyzed between ALL and NAT simulations to assess the human impact on the probability of occurrence of extreme events, defined as the ratio of the probability of exceeding observed events in ALL ($P_{ALL}$) and NAT simulations ($P_{NAT}$), that is, $RR_{ALL/NAT} = P_{ALL} / P_{NAT}$ (e.g., Fischer and Knutti 2015). The RR is also calculated between $P_{GHG}$ and $P_{NAT}$ for CMIP6 data to isolate the contribution of GHG forcing. All analyses are repeated using 2012 observations (the second highest hot-wet event based on the joint probability of June $T_{mean}$ and JA R50mm) to assess robustness of the attribution results to different thresholds (Stott et al. 2004). Univariate and joint probabilities of occurrence are calculated empirically by counting number of events exceeding the observed threshold(s) and then dividing it by the total number of samples. The “likelihood ratio method” (Paciorek et al. 2018) is employed to estimate the 5%–95% confidence intervals of RR.

Results.

For June $T_{mean}$, CMIP6 results show that $P_{ALL}$, $P_{GHG}$, and $P_{NAT}$ are 3.24%, 27.30%, and 0.81%, respectively (Table 1). The corresponding $RR_{ALL/NAT}$ and $RR_{GHG/NAT}$ are 4.00 [5%–95% confidence interval (CI) is 1.99–9.03] and 33.67 (CI 18.30–71.94), respectively, indicating robust human influences on extremely warm conditions in June, consistent with previous studies (Min et al. 2014, 2019, 2020; Kim et al. 2018). Although $P_{AER}$ is 0%, smaller $P_{ALL}$ than $P_{GHG}$ implies that aerosol forcing offsets the GHG-induced increases in probability of hot extremes, assuming other external forcings to be much less significant here. In contrast, JA R50mm shows very similar probability of extreme events across different forcings, ranging from about 3.1% to 5.3% (Table 1). The resulting $RR_{ALL/NAT}$ and $RR_{GHG/NAT}$ are 1.12 (CI 0.72–1.75) and 1.56 (CI 1.04–2.38), respectively, suggesting limited detectability of human influence on the changes in heavy precipitation over East Asia (e.g., Burke et al. 2016; Kawase et al. 2020; Sun et al. 2019; Zhang et al. 2020). The successive hot-wet extreme events simultaneously exceeding the observed June $T_{mean}$ and JA R50mm are expected to occur less frequently than univariate cases (Table 1). Indeed, CMIP6 results show that the joint probability of extreme events is zero in ALL, AER, and NAT (Fig. 2a), leading to the confidence interval of $RR_{ALL/NAT}$ undefined (Fig. 2c). 2020-like successive events are extremely rare even under greenhouse warming only ($P_{GHG} = 1.49\%$), resulting in unbounded $RR_{GHG/NAT}$ (CI 7.65–$\infty$).

HadGEM3-A results largely support CMIP6-based ones although they tend to exhibit higher $P_{ALL}$ and lower $P_{NAT}$ than CMIP6, which might be partly due to the different experiment setup (i.e., conditioned on the observed SST/SIC versus freely driven SST/SIC in CMIP6 coupled models). When considering June $T_{mean}$ only, $P_{ALL}$ and $P_{NAT}$ are 3.43% and 0.00%, resulting in unbounded (CI 12.84–$\infty$; Table 1). Note that $P_{ALL}$ and $P_{NAT}$ become 6.86% and 3.05% for JA R50mm only, which gives $RR = 2.25$ (CI 1.41–3.72), suggesting human-induced intensification of heavy precipitation. For the successive hot-wet extreme events, HadGEM3-A simulates $P_{ALL}$ and $P_{NAT}$ as 0.57% and 0.00% with unbounded (CI 1.76–$\infty$; Fig. 2c).

To take into account the limited number of events, particularly for $P_{NAT}$, the RR analysis is repeated using the 2012 observed threshold, namely the second highest successive events (note that $T_{mean}$ and R50mm have a similar return time of 6–7 years). As expected, $P_{ALL}$, $P_{GHG}$, and $P_{NAT}$ are increased overall and provide more stable RR results with reduced uncertainty ranges (Table 1). Although $P_{AER}$ remains 0% due to the strong aerosol cooling effect, $P_{ALL}$ remains lower than $P_{GHG}$, confirming the offsetting effects of aerosols. CMIP6 results show that
Table 1. Probability of occurrence (for June $T_{\text{mean}}$, JA R50 mm, and both combined) exceeding the observed 2020 and 2012 thresholds and corresponding RR values. Parentheses indicate 5%–95% uncertainty ranges of RR estimated from the likelihood ratio method (Paciorek et al. 2018).

<table>
<thead>
<tr>
<th>Observed year</th>
<th>Variable(s)</th>
<th>Probability of occurrence</th>
<th>CMIP6</th>
<th>HadGEM3-A-N216</th>
</tr>
</thead>
<tbody>
<tr>
<td>2020</td>
<td>June $T_{\text{mean}}$</td>
<td>$P_{\text{ALL}}$</td>
<td>3.24%</td>
<td>3.43%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$P_{\text{GHG}}$</td>
<td>27.30%</td>
<td>—</td>
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<tr>
<td></td>
<td></td>
<td>$P_{\text{NAT}}$</td>
<td>0.81%</td>
<td>0.00%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$P_{\text{AER}}$</td>
<td>0.00%</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>JA R50 mm</td>
<td>$P_{\text{ALL}}$</td>
<td>3.78%</td>
<td>6.86%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$P_{\text{GHG}}$</td>
<td>5.27%</td>
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<td></td>
<td></td>
<td>$P_{\text{NAT}}$</td>
<td>3.38%</td>
<td>3.05%</td>
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<tr>
<td></td>
<td></td>
<td>$P_{\text{AER}}$</td>
<td>3.11%</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>June $T_{\text{mean}}$ and JA R50 mm</td>
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<td>0.57%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$P_{\text{GHG}}$</td>
<td>1.49%</td>
<td>—</td>
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<td></td>
<td></td>
<td>$P_{\text{NAT}}$</td>
<td>0.00%</td>
<td>0.00%</td>
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<tr>
<td></td>
<td></td>
<td>$P_{\text{AER}}$</td>
<td>0.00%</td>
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</tr>
<tr>
<td></td>
<td></td>
<td>$R R_{\text{ALL/NAT}}$</td>
<td>1.12 (0.72–1.75)</td>
<td>2.25 (1.41–3.72)</td>
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<tr>
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<td></td>
<td>$R R_{\text{GHG/NAT}}$</td>
<td>1.56 (1.04–2.38)</td>
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</tr>
<tr>
<td>2012</td>
<td>June $T_{\text{mean}}$</td>
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<td>$P_{\text{GHG}}$</td>
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<td>$P_{\text{AER}}$</td>
<td>0.00%</td>
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</tr>
<tr>
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<td>JA R50 mm</td>
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<td></td>
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<td>8.78%</td>
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</tr>
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<td>June $T_{\text{mean}}$ and JA R50 mm</td>
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<td>4.76%</td>
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<td>$P_{\text{GHG}}$</td>
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<td>—</td>
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<tr>
<td></td>
<td></td>
<td>$P_{\text{NAT}}$</td>
<td>0.81%</td>
<td>0.00%</td>
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<tr>
<td></td>
<td></td>
<td>$P_{\text{AER}}$</td>
<td>0.00%</td>
<td>—</td>
</tr>
<tr>
<td></td>
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<td>$R R_{\text{ALL/NAT}}$</td>
<td>3.17 (1.54–7.25)</td>
<td>∞ (18.03–∞)</td>
</tr>
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<td></td>
<td></td>
<td>$R R_{\text{GHG/NAT}}$</td>
<td>10.00 (5.28–21.76)</td>
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</table>
= 3.39 (CI 2.68–4.34) and = 9.02 (CI 7.30–11.34) for June $T_{\text{mean}}$. Smaller RRs indicate that human influence is weaker in less extreme heat events, in line with previous studies (e.g., Kharin et al. 2018; Min et al. 2020). For JA R50mm, $P_{\text{ALL}}, P_{\text{GHG}},$ and $P_{\text{NAT}}$ increase 9.46%, 12.57%, and 9.19%, respectively, but RRs remain similar to the 2020-based results, supporting generally much weaker signal detectability in precipitation extremes. The probabilities of 2012-like
successive hot-wet extreme events become 2.57%, 8.11%, and 0.81% in ALL, GHG, and NAT, respectively. The corresponding is 3.17 (CI 1.54–7.25), indicating that the risk of 2012-like hot-wet summer event has increased about 3 times due to human impacts (Fig. 2c). HadGEM3-A results also show increased probabilities of occurrences when applying the lower observed threshold. In univariate cases, \(P_{\text{ALL}}\) and \(P_{\text{NAT}}\) are 33.33% and 0.76% for June \(T_{\text{mean}}\) with = 43.75 (CI 21.13–113.65) and 16.00% and 8.76% for JA R50mm with = 1.83 (CI 1.38–2.44). However, bivariate probability remains rare with \(P_{\text{ALL}} = 4.76\%\) and \(P_{\text{NAT}} = 0.0\%\), resulting in unbounded (18.03–∞). HadGEM3-A results using the 2012 threshold need to be interpreted with caution due to its experiment setup (i.e., the 2020 observed SST/SIC was prescribed).

It is useful to check RR values for different \(T_{\text{mean}}\) and R50mm thresholds that can occur in the future. For this purpose, RR values are also calculated for hypothetical values of normalized June \(T_{\text{mean}}\) from 0 to 3 and JA R50mm from 3 to 6 using CMIP6 simulations (Fig. 2d). These thresholds are constructed by linearly connecting the 2012 and 2020 observed events (solid line in Fig. 2a), thus having different rarity between \(T_{\text{mean}}\) and R50mm (see above). Resulting RR curves indicate an overall increase in RR as more-extreme thresholds are applied for both ALL and GHG, which demonstrates that greenhouse warming will have a stronger impact on successive hot-wet extremes with higher intensities, reaffirming previous studies (Zhou and Liu 2018; Vogel et al. 2020). It is also noteworthy that future aerosol reduction compared to a recent baseline (Wilcox et al. 2020) may enhance warming over South Korea and add further to the GHG-induced increase in hot-wet extreme events.

**Concluding remarks.**

CMIP6 multimodel and HadGEM3-A high-resolution large-ensemble simulations consistently indicate significant increases in the likelihood of the 2020-like successive hot-wet extreme summers due to anthropogenic greenhouse gas forcing, with impacts for society and ecosystems. Given the uncertainty due to limited model skill, further investigation is warranted using higher-resolution models, which can better simulate local-scale heavy precipitation events. Interconnections and driving factors of successive hot-wet extreme events remain unclear and need to be explored.

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References


The 2020 Record-Breaking Mei-yu in the Yangtze River Valley of China: The Role of Anthropogenic Forcing and Atmospheric Circulation

Chunhui Lu, Ying Sun, and Xuebin Zhang

Anthropogenic forcing has likely reduced the probability of the 2020 June–July mei-yu in the Yangtze River Valley by approximately 54%; however, the anomalous circulation of 2020 favored the occurrence of heavy precipitation.

The Chinese mei-yu is a period of intense precipitation during the East Asian rainy season, and typically provides the majority of June–July precipitation in the middle to lower Yangtze River Valley (YRV) (Ding and Chan 2005). In 2020, the YRV experienced a record-breaking mei-yu, characterized by a heavy and persistent precipitation, a wide meridional rain belt, and frequent heavy rainstorms (Ding et al. 2021). The June-to-July total precipitation amount in the mei-yu region was about 672 mm, 99% more than the 1961–90 average and the highest on record since 1960 in the region. The mei-yu lasted for 62 days, with 74 stations experiencing record-breaking total precipitation amounts and over 600 rivers across China exceeding their warning water levels (CMA 2021). The resulting disasters, including flooding and landslides, affected more than 30 million people and 3.58 million hectares of crops in the YRV, resulting in a direct economic loss about 132.2 billion Chinese Yuan (CMA 2022).

A few studies have investigated the circulation pattern of the 2020 mei-yu and the possible drivers of it. The anomalous persistent western North Pacific subtropical high (WNPSH) and the southwesterly jet on its western side was found to be the dominant circulation pattern of the 2020 mei-yu in the Yangtze River Valley (YRV).
pattern during this event, which was caused by both La Niña–like sea surface temperature (SST) anomaly in the equatorial Pacific and warm SST anomaly in the tropical Indian Ocean (Liu and Ding 2020; Ding et al. 2021; Pan et al. 2021). The Tibetan Plateau vortices (TPVs) may be another possible contributor by transforming the positive vorticity into troughs and moving eastward to modulate the precipitation in the YRV (L. Li et al. 2021). These studies suggest the important role of natural factors internal to the climate system including SST variation in the 2020 mei-yu. However, the role of anthropogenic external forcing in the summer 2020 mei-yu has not been extensively evaluated. Previous studies (Li et al. 2018; Zhou et al. 2018) have shown that the strong El Niño of 2015/16 may account for the extreme precipitation event in the YRV during 2016 summer while anthropogenic effects can be only found on smaller spatial scales. A few studies (Burke and Stott 2017; Lu et al. 2020; X. Li et al. 2021) proposed that human-induced warming and natural variation played important roles in the changes in intensity and frequency of extreme precipitation in the YRV. Here, we investigate how externally forced factors and synoptic circulation conditions may have affected the 2020 mei-yu event based on simulations from phase 6 of the Coupled Model Intercomparison Project (CMIP6; Eyring et al. 2016).

Data and methods.

The mei-yu region (28°–34°N, 110°–122.5°E; black box in Fig. 1a) defined by the China Meteorological Administration (CMA 2017) was selected as the key study region. Daily precipitation data at 414 stations in the region for 1960–2020 were extracted from a homogenized observational dataset developed by the China National Meteorological Information Center (Yang and Li 2014). Two metrics, including percentage precipitation anomaly (PPA) and maximum five-consecutive-day precipitation anomaly (RX5day, relative to the 1961–90 average) from June to July were used to describe different characteristics of 2020 mei-yu. The observed precipitation and RX5day at each station were first averaged onto the grid boxes of 2° × 2° and then averaged to obtain the area-weighted regional mean precipitation in the mei-yu region. The PPA was then calculated by the anomaly of regional mean precipitation divided by the 1961–90 average. The NCEP–NCAR reanalysis data (Kalnay et al. 1996) were used for the investigation of atmospheric circulation changes, including 500-hPa geopotential height (Z500) and 850-hPa zonal and meridional winds (UV850).

For the model results, PPA and RX5day were calculated similar to observation based on 53 runs of nine CMIP6 models under historical (natural + anthropogenic) forcings (ALL) and 49 runs under natural-only (NAT) forcing, respectively (see Table S1 in the online supplemental material). We extended the historical ALL forcing runs to 2030 with the Shared Socioeconomic Pathway SSP2–4.5 scenario (2015–30). The SSTs and atmospheric and land conditions of CMIP simulations are not synchronous with observations, so using CMIP simulations to evaluate a specific year is not possible. Thus, we selected the period of 2001–20 as present-day climate. We did not select the period 2011–30 centered on the year of the event, as the NAT-forcing run ends in 2020. This slightly affects our attribution results. Given the small recent trends in precipitation in the mei-yu region (Ding et al. 2020), the recent two decades (2001–20) reasonably represent current climatic conditions, as also assumed in other studies (Christidis and Stott 2015).

To estimate the anthropogenic influence on the 2020 mei-yu, we calculated the probabilities of events exceeding the threshold of 2020-like mei-yu for the ALL and NAT forcing experiments, that is, both with (P_{ALL}) and without (P_{NAT}) the effect of anthropogenic influence. The 2020 thresholds for both PPA (99.6%) and RX5day (71.2 mm) were first adjusted by the method used in Sun et al. (2018) because the limitations of current generation of climate models to reproduce the very heavy precipitation (see details in the online supplemental material). The adjusted thresholds for PPA and RX5day are 51.2% and 57.1 mm respectively. The kernel
Fig. 1. (a) Percentage precipitation anomaly (PPA, %) in 2020 June–July and (b) RX5day anomaly (mm) in 2020 June–July for observations in 2020. (c), (d) Regional PPA (%) and RX5day anomaly (mm) in June–July for observations (black), ALL simulations (red), and NAT simulations (blue) for 1960–2014. Thick lines denote ensemble mean, and shading denotes the 5%–95% ranges of the individual model simulations. (e) Geopotential height (red contours; gpm) at 500 hPa and winds (blue vectors; m s⁻¹) at 850 hPa in June–July of 2020 based on reanalysis data. (f) Z500 (gpm) and UV850 (m s⁻¹) in June–July of 2001–20 based on the mean of June–July extracted from the CMIP6 results with the ALL experiment, for which the circulation pattern correlates well (coefficient greater than 0.7) with the 2020 reanalysis pattern over the region marked by the black box. The green line in (e) and (f) indicates the Yangtze River.
density estimation (KDE) was used to estimate the probability density distribution, which has been proved to be suitable to estimate the probability density functions (PDFs) of precipitation event (Ma et al. 2017; Lu et al. 2021). The probability ratio (PR) was then defined as \( PR_{Anthro} = \frac{P_{ALL}}{P_{NAT}} \). Uncertainties in PR were obtained using 1000 bootstraps, with PR computed for each bootstrap realization (Christidis et al. 2015).

To estimate the effects from atmospheric circulation, the method suggested by Christidis and Stott (2015) was used. We first selected the key circulation region that dominate this mei-yu event in the observation (i.e., the WNPSH region as shown in Fig. 1e). The anomalous WNPSH has been confirmed as the key circulation pattern driving the 2020 mei-yu, and reflects the joint influence from the anomalous SSTs in the equatorial Pacific and Indian Ocean (Pan et al. 2021). Then we partitioned simulated June–July Z500 from all models and years (2001–20) under ALL forcing into two groups (Table S2): one that is highly correlated (correlation coefficients above 0.7) with the observed Z500 in 2020 over the key WNPSH region, and one that is less correlated (correlation coefficients below 0.7) with observed Z500. For these two high-correlation and low-correlation groups, the probabilities of events exceeding the 2020-like threshold value \( \left(P_{High} \text{ and } P_{Low}\right) \) were calculated respectively based on KDE. The probability ratio for the circulation effects was defined as \( PR_{Circ} = \frac{P_{High}}{P_{Low}} \). Uncertainties in PR was estimated as those used in the analysis for the anthropogenic influence. We also conducted sensitivity test for different coefficients from 0.6 to 0.8, and found negligible influence on the final results (Fig. S2a).

Results.
Figure 1a shows that the observed June–July positive PPA was centered in the YRV. In the mei-yu region, the PPA in most stations was more than 50% and 74 stations experienced the record-breaking precipitation. The RX5day anomaly at nearly half of the stations was greater than 100 mm, with the maximum value reaching 435.5 mm. Figures 1c and 1d show the temporal evolutions of observed and model simulated PPA and RX5day anomalies over the mei-yu region from June to July. It is apparent that June–July 2020 was the wettest on record since 1960, with PPA and RX5day both reaching the highest values. This extreme precipitation was associated with the low-level southwesterly winds on the western side of the WNPSH, which continuously transport water vapor into the YRV (Fig. 1e). Figure 1f displays the model ensemble mean of Z500 and UV850 in June–July from the high-correlation group during the current climate state of 2001–20 under ALL experiments. The extended WNPSH and the obvious southwesterly flow on its western side, which is similar to the observed circulation pattern, provide favorable conditions for heavy precipitation events.

Figures S1a and S1b in the online supplemental material show the histogram and KDE estimate of the probability distribution of the observed and simulated June–July PPA and RX5day anomalies during 1960–2014. The models reasonably simulate the probability distribution for PPA and RX5day over the mei-yu region, with quite similar shapes between observation and models. Figures S1c and S1d show the \( p \) values from Kolmogorov–Smirnov tests that compare the observed distribution with multimodel ensemble and individual models. The agreement remains good for both PPA and RX5day when models are tested individually. This suggests that the models can be used to conduct the attribution analyses.

To investigate human influence on the mei-yu event, we compared the CMIP6 model experiments under ALL and NAT forcings. For PPA, the PDF shift toward a drier condition under ALL forcing relative to NAT forcing (Fig. 2a), suggesting a decrease of probability of such persistent heavy precipitation events over the YRV due to human influence. The probability of the 2020-like event defined by PPA (51.2%) is around 1.78% (90% confidence interval: 1.28%–2.38%) in the ALL ensemble, while in the NAT ensemble the probability increases to 3.29% (2.56%–4.12%). This gives a probability ratio of 0.54 (0.36–0.81). For the RX5day, the
Fig. 2. The impact of the anthropogenic forcings and 2020 mei-yu circulation pattern on the 2020-like mei-yu, showing the June–July (a) PPA and (c) RX5day anomaly distributions from model experiments with (red contours) and without anthropogenic forcings (blue contours); the June–July (b) PPA and (d) RX5day anomaly distributions in the high-correlation ensemble (orange contours) and low-correlation ensemble (green contours) based on CMIP6 ALL results; and (e) the changes in the probability due to anthropogenic forcings and (f) the changes in the occurrence probability of 2020-like mei-yu of under the influence of a 2020-like circulation pattern. Best estimates of the change in the probability are marked by the square symbols and the 5%–95% uncertainty range by the vertical whiskers.
PDF shows almost no change for both experiments. The probability ratio for the 2020-like RX5day anomaly (57.1 mm) is 0.95 (0.5–1.61), indicating little anthropogenic influence on this metric. Previous studies proposed two competing effects of anthropogenic forcing on the precipitation in East Asia. One is the effect of increased moisture caused by global warming (Trenberth et al. 2003) and the other is the cooling effect induced by the increased anthropogenic aerosols. The latter could weaken the thermal differences between land and ocean, and thus reduce the East Asian summer monsoon (EASM), decreasing the likelihood of persistent heavy precipitation (Song et al. 2014; Li et al. 2015; Rimi et al. 2019). Therefore, for the June–July PPA that mostly represents the persistent precipitation, anthropogenic forcing has likely reduced the probability of the similar events. But for the extreme rainfall (RX5day), the aerosol effects may be counteracted by the increased moisture induced by global warming, resulting in weak anthropogenic signal in quantitative analyses (Zhang et al. 2019).

We then analyzed the effect of circulation pattern on this event. We compared the PDFs of simulated precipitation between high- and low-correlation groups under ALL forcing (Figs. 2b,d). Both PPA and RX5day results show that the anomalous circulation increases the chance of heavy precipitation occurring. The PDFs of high correlation group shift toward a wetter regime compared with those for the low correlation group. The Kolmogorov–Smirnov test shows that the distributions from high- and low-correlation groups are significantly separated as the p values are near zero. The probability of the 2020-like PPA event is around 2.9% (with 90% confidence interval 1.7%–4.0%) in the high-correlation ensemble, while it decreases to 1.2% (0.6%–1.7%) in the low-correlation ensemble. This gives a probability ratio of 2.3 (1.2–5.2). For RX5day, the PDF shifts toward wetter regime in the high-correlation ensembles, with the occurrence probability increasing about 3.2 (1.3–5.6) times compared with that from the low-correlation group. This indicates the influence of persistent circulation on this mei-yu event. Further analyses indicate that these results are insensitive to the selection of critical area, as long as the southwesterly jet on the western side of the WNPSH is included in the area (Fig. S2b).

Conclusions.

For the 2020 record-breaking mei-yu, we analyzed both PPA and RX5day based on observations and CMIP6 models. We found that human influence tends to reduce the probability of PPA that represents the persistent precipitation, but has insignificant impacts on RX5day, which represents extreme heavy rainfall. The probability of the 2020-like persistent precipitation has decreased by about 54% under anthropogenic forcing, which is consistent with previous studies based on CMIP5 models and other large-ensemble models (Zhang et al. 2019; R. Li et al. 2021). However, we should keep in mind that the adjusted threshold for this event may cause the inaccurate estimate of the probability changes. For the effects of circulation pattern, the prevailing flow pattern along the WNPSH has increased the occurrence probability of 2020-like PPA and RX5day by about 2.3 and 3.2 times, respectively. As the key circulation system for the 2020 mei-yu, the anomalous strong WNPSH was jointly affected by the SST in the equatorial Pacific and Indian Ocean, which reflects important role of the SST changes. Although the CMIP6 models generally are able to simulate the long-term warming in the Pacific and the Indian Ocean, more detailed analyses about SST influence are needed in the future. Especially, understanding different roles of anthropogenic forcing and internal fluctuation of ocean in the SST changes could help separate the contribution from the different factors to the occurrence of precipitation.

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References


Toward Near-Real-Time Attribution of Extreme Weather Events in Aotearoa New Zealand

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A consortium, including the National Meteorological Service, is developing an operational capability to evaluate the human contribution to severity and frequency of extreme weather events affecting Aotearoa New Zealand.

The science of extreme weather event (EWE) attribution has developed rapidly since the case study of the European heatwave of 2003 (Stott et al. 2004). Since then, motivated by public and media interest in whether, and to what degree, climate change affects the severity and frequency of these events, significant advances have been made in providing attribution statements in near-real time [e.g., rapid studies by World Weather Attribution (Ciavarella et al. 2020; Vautard et al. 2019); see also Otto et al. (2018) and Philip et al. (2018)]. The Extreme Weather Event Real-time Attribution Machine (EWERAM) project, currently underway in Aotearoa New Zealand (NZ), aims to provide statements about human-induced changes to the frequency and/or severity of an EWE within days of an event. Recognizing the need for a broad range of skills, EWERAM team members have been recruited from research institutions [Bodeker Scientific and the National Institute of Water and Atmospheric Research (NIWA)], the National Meteorological Service of New Zealand (MetService), and academia (Victoria University of Wellington, University of Canterbury). As we work toward making EWERAM operational, MetService’s well-established communication channels will

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be used to publicly disseminate attribution statements. An overarching goal of EWERAM is to enhance the general understanding of NZ’s public as to how climate change is affecting their lives here and now.

In NZ, aside from major earthquakes, intense rainfall events incur the greatest insured losses from natural disasters (ICNZ 2021). EWERAM thus focuses on extreme precipitation events in addition to temperature-related extreme events. Attribution of large-scale EWEs over NZ can be achieved through well-developed approaches that analyze global or regional climate model simulations (Christidis et al. 2014; Philip et al. 2020; Rosier et al. 2015). However, for NZ with its fine-scale topography (mountain ranges rise from sea level to over 3000 m within a horizontal distance of about 20 km), conducting climate model simulations at the scales required to resolve orographically forced precipitation extremes is computationally prohibitive. Accordingly, and given available expertise and infrastructure, EWERAM has taken a “two-stream” approach to attribution that (i) assesses changes in the frequency and severity of events using large ensembles of simulations from the weather@home/Australia–NZ project, hereafter weather@home/ANZ (Black et al. 2016), and (ii) diagnoses changes in the severity of EWEs using a more highly conditioned approach where the large-scale, synoptic circulation underlying the event is prescribed in factual and counterfactual simulations using MetService’s well-tuned numerical weather prediction (NWP) model, which is used for operational predictions of NZ’s weather. The factual simulations represent the extreme event in the climate we currently experience while one counterfactual scenario simulates how the event would have evolved under colder, preindustrial climate conditions. Changes in the severity are typically reported as a percentage change for precipitation and as a total change in degrees Celsius for temperature-related events, while the change in frequency is reported as a probability ratio pointing out the percentage change this implies.

The generation of a large and diverse set of diagnostics for each target EWE has been automated so that an EWERAM expert group can convene while the event is still of public interest. The group examines these diagnostics, decides which further diagnostics and statistics are required, and, once sufficient information for a conclusive analysis has been collected, uses this scientifically defensible foundation as a basis for crafting an attribution statement.

**Approaches to attribution within EWERAM.**

An overview of EWERAM’s workflow is represented in Fig. 1. Once an event is selected, based on expert judgement by MetService meteorologists taking into account public and media interest, the project produces bespoke simulations using the Weather Research and Forecasting model (WRF; Skamarock et al. 2019) and a plethora of diagnostic plots and statistics based on these WRF simulations. In parallel, pre-existing climate model simulations from weather@home/ANZ are analyzed for selected regions. Once results from both streams are available, the EWERAM expert group convenes. At least one member from each area of expertise is required for decision making. The expert group uses analyses of observational data to define the spatial and temporal attributes of the event, to provide historical context to the event and to determine how well the NWP and climate models simulate the target event or class of events. Depending on the outcomes, a decision is made as to whether an attribution statement can be formulated based on pre-calculated statistics, whether further statistics (such as for an updated, carefully chosen event definition) are required prior to making a statement, or whether an attribution assessment is not possible as the methods or models are inadequate. Acknowledging that we will learn with every event analyzed, a retrospective assessment following every analyzed event enables continual improvements to be made to the processes. The two streams used for attribution within EWERAM are described below.
**Fig. 1. Flowchart of the processes used within EWERAM for EWE attribution.**

Severity attribution using a numerical weather prediction model. How the severity of an event may have changed can be estimated using simulations from an initialized NWP model configured similar to that described in Reed et al. (2020). At MetService, the WRF model is initialized close to the time of the event using fields from the Global Forecast System (GFS) as boundary conditions. Three WRF-based experiments are defined (see also Fig. 2):

1) The factual (here ALL) experiment, which is similar to the operational forecast, but does not assimilate observations.
2) The counterfactual, naturalized (here NAT) experiment, in which GFS’s sea surface temperature, air temperature, specific humidity, and geopotential height are adjusted using the benchmark estimate of the role of total anthropogenic forcing used in the International CLIVAR C20C+ Detection and Attribution Project (Stone and Pall 2021).

3) The counterfactual ALL+ experiment, in which C20C+ attributable change fields are added to (in contrast to NAT where they are subtracted from) the GFS boundary conditions to test for consistency as suggested in Philip et al. (2020).

For each experiment, in addition to a single deterministic simulation, a 21-member ensemble is initiated. The ALL ensemble is then validated against observations to determine if WRF simulations reproduce the event, which is a prerequisite for any attribution analysis.

Severity and frequency attribution using climate model simulations. As EWEs in NZ are affected by changes in large-scale dynamics, we exploit the large attribution ensembles of regional climate model simulations from the weather@home/ANZ project to determine how the likelihood and severity of an event has changed between factual (natural and anthropogenic forcing included, i.e. ALL) and counterfactual (natural forcing only, i.e., NAT) realizations using an approach similar to Rosier et al. (2015) and following well-established probabilistic approaches to event attribution. To accommodate any biases in the weather@home/ANZ simulations, we

Fig. 2. A schematic diagram of the key aspects of severity attribution conducted within EWERAM using three 21-member ensembles of WRF (plus one deterministic run per ensemble). The ALL ensemble represents factual conditions, while the boundary conditions are adjusted by subtracting an attributable warming estimate to mimic naturalized conditions in the counterfactual NAT ensemble. An adjustment in the opposite direction provides the counterfactual ALL+ ensemble that is used as a sanity check. A remaining research question is highlighted. Note that the horizontal spread from a range of applied deltas has not yet been implemented.
use the return period of the observed event to find the threshold in factual weather@home/ANZ simulations with the same return period (Philip et al. 2020; van Oldenborgh et al. 2021) and then use that threshold in further analyses. We acknowledge, however, the need to extend the analysis to include the use of other climate models [as done, e.g., in Philip et al. (2020)] to understand the robustness of results.

Lessons learned and remaining challenges.

While attempting to provide timely attribution statements using expert judgment and modeling infrastructure across several NZ-based organizations has proven challenging, EWERAM has provided insights and advanced our capabilities. For example, we have developed the capability to create factual and counterfactual ensembles using WRF, which may, in addition to their intended use in event attribution, prove valuable to drive hydrological models. Recognizing that incorporating as many sources of uncertainty as possible is necessary to have confidence in any attribution statement, we have explored how to incorporate physical parameterization uncertainties and numerical scheme uncertainties (see Duda et al. 2016) into the WRF simulations (vertical spread from perturbation schemes in Fig. 2). A remaining challenge for incorporating uncertainties into WRF ensembles is to include additional attributable warming estimates to sample across the physically plausible range (horizontal spread resulting from a range of applied deltas within NAT and ALL+ in Fig. 2).

Despite the logistic complications entailed, the formulation of attribution statements requires contributions from all areas of expertise within EWERAM achieved by way of expert group meetings. We have learned that availability of a plethora of precalculated diagnostics from model simulations and observations is essential to expert group diagnoses of the characteristic of the target EWE. We have found that the two-stream approach is valuable in gaining a better understanding of the impact of climate change on the event. Attribution analyses of several extreme events analyzed within EWERAM found no systematic differences in the results obtained from different levels of conditioning (Stone et al. 2021, manuscript submitted to Wea. Climate Extremes). While the cross-institutional team is characteristic of EWERAM, we note that the size of the team limits how soon after an event an attribution statement can realistically be agreed upon. We expect the process to become more streamlined as we work through further events.

EWERAM is an ambitious project, and some research questions are yet to be resolved. For example, we need to analyze WRF simulations from further events to decide how we deal with individual ensemble members that do not represent the observed EWE well (see also Fig. 2). Another challenge that remains is how best to communicate a coherent public message regarding the attribution of an event when several lines of evidence (see, e.g., van Garderen et al. 2021) may result in a nuanced conclusion that cannot easily be digested by non-experts.

Conclusions and outlook.

EWERAM has developed a system that uses two approaches for event attribution: one based on relatively coarse-resolution climate model simulations that can be analyzed using traditional probabilistic approaches to attribution, and one based on much finer-scale simulations using an NWP model constrained to the prevailing synoptic situation, which can be used to determine changes in the severity of an event. Analyzing simulations for these different levels of conditioning enables analyses of a wider range of events. Looking forward, the goal of EWERAM is to move from the research phase into a pre-operational phase of internal testing, and then to become an operational capability. Achieving this is a challenge in NZ where there is limited financial support for such long-term collaborative activities. Combining the scientific expertise available at research institutions with the operational capabilities of a National Meteorological Service has been a strength of this project. Future delivery of a high-quality
timely EWE attribution service that benefits NZ’s public and other stakeholders will require continued support for a team that combines detection and attribution expertise and operational discipline.

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References


Heavy Rainfall Event in Mid-August 2020 in Southwestern China: Contribution of Anthropogenic Forcings and Atmospheric Circulation

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Atmospheric circulation explained about 47% of the observed intensity of the heavy rainfall event in mid-August 2020 in southwestern China, and anthropogenic forcings have roughly doubled the likelihood of such heavy rainfall.

Persistent heavy rainfall occurred in the Sichuan Basin and adjacent areas in southwestern China (Figs. 1a,b) during 11–20 August 2020, which was selected as one of the top 10 weather and climate events (http://news.weather.com.cn/2020/12/3427356.shtml) as well as one of the top 10 national natural disasters of 2020 in China (http://www.mem.gov.cn/xw/yjglbgzdt/202101/t20210102_376288.shtml). The average 24-h precipitation anomaly in southwestern China (25°–35°N, 98°–108°E) broke the record that had stood since 1960 (Fig. 1c). In terms of geographic range, intensity, and persistence, such a rainfall event has rarely been seen. The maximum 1-day precipitation amount broke the record at five stations in the Sichuan Basin, among which Lushan station witnessed a 1-day precipitation total of 425.2 mm, which was more than twice the previous record. The persistent heavy rainfall induced catastrophic flooding, which was at a one in 100 years level for Qingyi River on 17–18 August (http://news.weather.com.cn/2020/12/3427356.shtml). It also induced water-logging and mudslide disasters, which led to suffering for 8.523 million people, among which 58 sadly died and 13 are recorded as missing. Approximately 58,000
Fig. 1. Various characteristics averaged over 11–20 Aug 2020. (a) Spatial distribution of observed precipitation anomalies (unit: 100 mm) in 2020, in which the brown box (25°–35°N, 98°–108°E) is the target research area. (b) Rank of precipitation in 2020 in the historical record since 1960. (c) Precipitation anomaly averaged over the target region shown in (a) from 1960 to 2020 (black dots, with 2020 in red), in which the dark blue line indicates the observed value in 2020 and the light blue line and red line indicate the linear and nonlinear trend, respectively. (d) Return period fitted by using the GEV distribution. (e) Circulation anomalies for SLP (shading; unit: hPa) and Z\textsubscript{500} (contours; unit: gpm) in 2020, in which the blue box, red box, and entire map indicate the small domain size (20°–35°N, 110°–138°E), the medium domain size (20°–40°N, 97°–138°E), and the large domain size (15°–55°N, 70°–140°E) used for calculating the flow analogs, respectively. (f) Column-integrated moisture flux convergence from the surface to 300 hPa [shading; units: 10\textsuperscript{-4} kg (s m\textsuperscript{-1})]\textsuperscript{-1} and related moisture flux anomalies [vectors; unit: kg (s m\textsuperscript{-1})].
ha of crops were destroyed and the direct economic losses reached 60.93 billion Chinese Yuan (http://www.mem.gov.cn/xw/jg/202102/20210202_376288.shtml).

Attribution of heavy precipitation events in the complex East Asian summer monsoon region is difficult. Several studies have been carried out in eastern China and identified positive human influences (Burke et al. 2016; Sun and Miao 2018; Zhou et al. 2018; Sun et al. 2019) but also negative human influences (e.g., Zhang et al. 2020; Li et al. 2021). There are few studies that have quantified both the contribution of anthropogenic forcings and atmospheric circulation to an extreme precipitation event, although Ye and Qian (2021) attempted to quantify the contribution of both climate change and atmospheric circulation to the record-breaking precipitation event in East China in summer 2020 based on reanalysis data and fixing the circulation to the observations.

In this study, we first estimated the contribution of atmospheric circulation to the intensity of the record-breaking extreme rainfall event that occurred in southwestern China during 11–20 August 2020 using the flow analog method from a storyline perspective (Shepherd 2016). Then, we conducted an attribution analysis to quantify the contribution of anthropogenic forcings to the frequency of events of similar or higher intensity during 11–20 August from a probability-based perspective (Stott et al. 2004) by using the attribution simulations of the Met Office atmospheric general circulation model (Ciavarella et al. 2018).

Data.
This study used observational 24-h precipitation from 640 stations from the Daily Dataset of Surface Climatic Data of China (V3.0) (http://data.cma.cn/) for the period 1960–2020. The reanalysis data from the NCEP–NCAR Reanalysis I dataset (Kalnay et al. 1996) for the period 1960–2020 were used to analyze the circulation pattern and calculate the flow analogs. We also used model simulations with and without anthropogenic forcings (historical and historicalNat, respectively) from the latest Met Office attribution system, HadGEM3-GA6-N216 (Ciavarella et al. 2018). The 15 members of the historical simulation for 1960–2013 were used to evaluate the model performance, and 525 members for 2020 (historicalExt and historicalNatExt, respectively) were used to estimate the contribution of anthropogenic forcings to similar events.

Methods.
The persistent heavy rainfall event was defined by the rectangular area shown in Fig. 1a. Anomalies of station observational precipitation data were calculated relative to the base period of 1981–2010 and then interpolated into a 1° × 1° grid box, where the number of stations was typically 1 but could be up to 3 within a grid box. The area-weighted average was then calculated to obtain the regional-averaged time series (hereafter $P_{region}$) for 11–20 August. The linear trend and corresponding statistical significance in $P_{region}$ summed from these 10 days (Fig. 1c) were estimated by the nonparametric Wang and Swail (2001) iterative method with further consideration of repeat values in significance testing (Qian et al. 2019). The nonlinear trend was also considered and fitted based on the quadratic polynomial. We fitted this $P_{region}$ by using the generalized extreme value (GEV) distribution to calculate the return period (Fig. 1d).

First, the contribution of atmospheric circulation resembling 2020s to the intensity of this event was quantified by applying the method described in Ye and Qian (2021). The method was refined based on the flow analog method (You et al. 2007; Jézéquel et al. 2018), which is used to estimate the climatic conditions from historical days with large-scale synoptic atmospheric circulation similar to the day of interest and to reconstruct the event of interest. The steps of the method are briefly listed in the online supplemental material. After carrying out parameter sensitivity tests (Fig. S1 in the online supplemental material), we determined that the number of analogs selected was 10 (Fig. S1a); the region used to calculate the analogs was
the medium domain 20°–40°N, 97°–138°E (Fig. S1b), which included the intensified western Pacific subtropical high (WPSH) and the water vapor convergence zone to the west of the WPSH (Figs. 1e,f); the flow variable selected was sea level pressure (SLP), after comparison with surface pressure (SP) and geopotential height at 500 hPa (Z500) (Fig. S1c); and the similarity between atmospheric circulation patterns was best measured by the spatial Pearson correlation coefficient (Fig. S1d).

After a rough investigation of the role of climate change through comparing precipitation anomalies reconstructed from the analogs from an earlier period and a later period using the method described in Ye and Qian (2021), we then used model simulations to quantify the contribution of anthropogenic forcings to the frequency of such events. To correct the model bias in the climatology (Zhang et al. 2020), $P_{\text{region}}$ was normalized and expressed as a percentage anomaly relative to the 1961–90 climatology (each individual day for 11–20 August). We then fitted the normalized $P_{\text{region}}$ averaged over 11–20 August using the GEV distribution to estimate the occurrence probability of extreme events exceeding the intensity of the 2020 event (as a threshold) in the presence and absence of anthropogenic forcings ($P_i$ and $P_o$, respectively). The GEV fittings in this paper were validated through quantile–quantile plots. The fraction of attributable risk (FAR; $1 - P_o/P_i$) (Stott et al. 2004) was calculated to evaluate the contribution of anthropogenic forcings to the occurrence probability of such events. The 95% uncertainty range of FAR was estimated by using 475 random subsamples of 525 model runs, 1,000 times, similar to the approach in Barriopedro et al. (2020).

**Results.**
The intensity of this event was 2.5 standard deviations ($\sigma$), with a return period of 306 [57, ∞] years (Fig. 1d). This event occurred under the background of a slightly linear decreasing trend (Fig. 1c) at a rate of $-1.9 (-5.0, 1.8) \text{mm decade}^{-1}$, which is not statistically significant. The nonlinear trend showed a transition around the mid-1980s from an increasing to a decreasing trend (Fig. 1c). These trends are largely overshadowed by variability.

Our target domain is located toward the eastern edge of the Tibetan Plateau and to the west side of the anomalously strong and persistent WPSH (Fig. 1e). Sufficient water vapor from the south was repeatedly transported to the research area and converged there (Fig. 1f). This circulation pattern was closely related to the persistent heavy rainfall event.

Flow-analog analysis demonstrates the important role of atmospheric circulation to the extreme precipitation (Fig. 2a). A rainfall event with intensity reaching or exceeding that of the 2020 event barely occurred under totally random circulation (hereafter Control-1, which means analogs were picked randomly within the sampling interval). It was also rare (ranking in the 98th percentile) in the reconstructed anomalies based on analogs. After considering the persistence in the atmospheric circulation (hereafter Control-6, which means atmospheric circulation persisted for 6 days in this region and analogs in the adjacent 6 days were not repeatedly picked), atmospheric circulation was found to explain 47.2% of the intensity of the observation (Fig. 2a), as estimated by dividing the difference between the median of the flow-conditioned anomaly and that of Control-6 by the observed anomaly, as in Jézéquel et al. (2018). Therefore, atmospheric circulation alone cannot explain this event. The comparison between precipitation anomalies reconstructed from the analogs from two periods suggests that under similar atmospheric circulation conditions, climate change has increased the likelihood of such heavy precipitation (Fig. 2b).

Before using model simulations to quantify the contribution of anthropogenic forcings, we first evaluated the model simulations of the normalized $P_{\text{region}}$ time series and the corresponding distributions for the period 1960–2013. The observations were found to lie within the range of the model simulations (Fig. 2c). The forced response to the ensemble mean of 15 historical simulations (roughly representing external forcings; hereafter Hist) tended to
Fig. 2. (a) Probability distributions of flow-conditioned $P_{\text{region}}$ on 11–20 Aug 2020 in southwestern China, as estimated through the flow-analog method. The three boxes indicate the simulated detrended $P_{\text{region}}$ (unit: mm) using random days (left), random days subsampled every six days to correct for serial dependence (middle), and analogs (right), respectively. (b) GEV distributions fitted to flow-conditioned precipitation anomalies in the past (1960–84; blue) and present (1985–2019; red) climate. (c) Time series and (d) distribution of the normalized $P_{\text{region}}$ in the observation and in model simulations for the period 1960–2013, and (e) the corresponding attribution through comparing model simulations with and without anthropogenic forcings for 2020. In (c), the shaded area indicates the range of 15 members. The dashed line indicates the corresponding linear trend. In (e), shaded areas indicate the 5%–95% uncertainty range. The FAR values (gray line) were calculated based on the thresholds shown in the abscissa. The red line in (a) and the black dashed line in (b) and (e) represent the observed value in 2020.
reduce the precipitation in terms of the linear trend, as compared with that of 15 historical-Nat simulations (roughly representing natural forcing; hereafter HistNat) (Fig. 2c). This partly explains the weak decreasing trend shown in Fig. 1c. A Kolmogorov–Smirnoff (KS) test suggested that there was no significant difference between the rainfall distributions from the historical simulation and that from the observations (KS test p value = 0.96) (Fig. 2d). Comparison between model simulations for 2020 with and without anthropogenic forcings suggests that anthropogenic forcings increase the occurrence probability of heavy rainfall with intensity exceeding that of 2020 (Fig. 2e). The FAR was calculated to be 0.59 (0.35, 0.72) when the threshold was fixed as 2020 observations (Fig. 2e), and the corresponding risk ratio ($P_1/P_0$) was 2.4 (1.5, 3.6), which indicates the occurrence probability has increased by 2.4 times under anthropogenic forcings.

**Conclusions and discussion.**

Large-scale atmospheric circulation resembling that of 2020 was found to explain about 47% of the intensity of the record-breaking persistent heavy rainfall event that occurred during 11–20 August 2020 in southwestern China, as estimated by the flow analog method. The occurrence probability of events with intensity exceeding this one during 11–20 August was found to have roughly doubled due to anthropogenically forced climate change, as estimated using HadGEM3-GA6-N216 model simulations forced by the observed sea surface temperature/sea ice concentration and external forcings in 2020. This effect is caused by an increase in variability (Fig. 2e and Fig. S2) rather than a long-term trend in the regional precipitation (Figs. 1c and 2c). This is supported by a recent finding that the variability of precipitation has increased with global warming in most of the world’s areas, including the target area in this study (Zhang et al. 2021). Optimal fingerprinting analysis has also revealed that heavy (light to moderate) precipitation has tended to increase (decrease) under anthropogenic forcings in eastern China (Ma et al. 2017).

It should be noted that the study area (Fig. 1) was selected according to the reported regions that suffered at the hands of this event. It covered the whole of Sichuan Province. The choice of region has a minor effect on our main conclusions. In addition, the impact of soil moisture feedback on the intensity of the event warrants further study, since flow analogs cannot detect this effect (Jézéquel et al. 2018).

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