Detectable anthropogenic influence on summer compound hot events over China from 1965 to 2014

Xiaoxin Wang, Xianmei Lang and Dabang Jiang

1 Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing 100029, People’s Republic of China
2 Collaborative Innovation Center on Forecast and Evaluation of Meteorological Disasters, Nanjing University of Information Science and Technology, Nanjing 210044, People’s Republic of China
3 National Institute of Natural Hazards, Ministry of Emergency Management of China, Beijing 100085, People’s Republic of China

* Author to whom any correspondence should be addressed.
E-mail: jiangdb@mail.iap.ac.cn

Keywords: compound hot events, detection and attribution, anthropogenic influence, CMIP6, China

Abstract

Compared with independent hot days or nights, compound hot extremes have more adverse effects on society. In this study, hot extremes are categorized into three types: independent hot days, independent hot nights and compound hot events combining daytime and nighttime hot extremes based on daily maximum and minimum temperatures. Using observations from the gridded dataset CN05.1 and experiments undertaken with 22 Coupled Model Intercomparison Project Phase 6 (CMIP6) models, we analyze the observed changes in summer hot extremes and compare them with model simulations over China between 1961 and 2014 and then conduct detection and attribution analyses of changes in compound hot events between 1965 and 2014 utilizing an optimal fingerprinting method. The results show that clear upward trends in the frequency and intensity of the three types of hot extremes are observed over China, with the largest trend occurring in hot nights for frequency and in compound hot events for intensity. The CMIP6 multimodel mean responses to all forcings agree well with the observed changes in the frequency and intensity of the three types of hot extremes. Anthropogenic (ANT) forcing can be robustly detected and separated from the response to natural (NAT) forcing in the frequency and intensity trends of compound hot events over China, and the attributable contribution of ANT forcing is estimated to be much larger than that of NAT forcing. Further analyses on the model responses to NAT, greenhouse gas (GHG) and ANT aerosol (AER) forcings indicate that GHG forcing is detectable in the observed increased frequency of compound hot events. By contrast, NAT and AER forcings cannot be detected, and their effects on the observed changes in compound hot events over China are generally negligible.

1. Introduction

In recent years, hot extremes have occurred more frequently and with increased intensity as the global mean surface air temperature has risen (IPCC 2012, Luca et al 2020). Changes in hot extremes have exerted profound impacts on natural ecosystems, human health and the economy (Aström et al 2013, Mora et al 2017). Considerable efforts have been made to investigate the historical and future changes in hot extremes (Sillmann et al 2013, Zhou et al 2015, Sui et al 2018, Luca et al 2020, Liao et al 2021). Increases in warm extremes and decreases in cold extremes have been observed and are projected to generally continue during the 21st century at global and regional scales (Donat et al 2013, Xia et al 2017, Christidis et al 2020). Due to the presence of complex terrains, high population densities and its relatively inadequate infrastructure for disaster prevention, China is particularly vulnerable to climate extremes (Wang et al 2012). For example, the extremely hot summer and the accompanying drought in northeast China in 2016 caused damage of 15.6 billion RMB (Li et al 2018). Observations have shown significant increases in warm temperature extremes over recent decades across China (Lu et al 2016, Dong et al 2018), and several extremely hot summers have occurred in the last two decades (Sun et al 2014).
It is important to understand the observed changes in hot extremes and investigate the roles of external and natural forcings. Detection and attribution analyses are widely utilized to quantify anthropogenic (ANT) and natural (NAT) influences on observed long-term climate changes. The Fifth Assessment Report (AR5) by the Intergovernmental Panel on Climate Change (IPCC) concluded that the observed global-scale changes in the frequency and intensity of daily temperature extremes since the mid-20th century have very likely been due to human influence, and it is likely that human influence has doubled the probability of the occurrence of heat waves in certain locations (IPCC 2013). Christidis et al (2005) first used the optimal fingerprinting method to detect ANT influences on changes in temperature extremes at the global scale. Subsequent studies have indicated that the observed changes in temperature extremes are significantly affected by human activities at global and continental scales (Min et al 2013, Morak et al 2013, Christidis and Stott 2016, Kim et al 2016). In contrast, it is more difficult to distinguish external influences on climate change at the regional scale (Hegerl 2007, Stott et al 2010). Such attempts have been made to address regional temperature extremes, and the influence of human activities has been clearly detected (Zwiers et al 2011, Wen et al 2013, Dong et al 2018). Furthermore, the occurrence of certain extreme weather and climate events has been suggested to be closely related to human influences, such as the 2014 heat wave in Europe, the 2016 record-breaking high temperatures in Asia and the 2018 persistent nighttime heat wave over north-east China (Uhe et al 2016, Imada et al 2018, Ren et al 2020).

Based on extreme climate indices defined by the Expert Team on Climate Change Detection and Indices (ETCCDI; http://etccdi.pacificclimate.org/list_27_indices.shtml), an increasing number of studies have been conducted on the detection and attribution of temperature extremes over China. These studies have suggested that the changes in the intensity and frequency of temperature extremes (e.g. TXx, TNN, TX90p and TN90p) during recent decades can be largely attributed to ANT influences (Ren and Zhou 2014, Lu et al 2016, Yin et al 2017, Hu et al 2020). Detectable ANT influences on the changes in summer days, tropical nights, icy days and frosty nights on the Tibetan Plateau and over China during recent decades have also been found (Yin and Sun 2018, Wang et al 2018a, Yin et al 2019). In addition, Sun et al (2019) showed that in eastern China, ANT-induced global warming and urbanization can be simultaneously detected in the changes in nighttime temperature extremes (TN90 and TN10p), while the changes in daytime temperature extremes (TX90 and TX10p) are predominantly due to ANT-induced global warming. Furthermore, detection and attribution analyses for individual extreme events have also been conducted, and they have indicated that human activities significantly increase the probability of occurrence of extreme high-temperature events, such as the 2013 and 2017 summer heat waves in eastern China (Sun et al 2014, Chen et al 2019), the 2013 summer heat wave in western China (Ma et al 2017) and the 2014 hot spring in northern China (Song et al 2015).

The aforementioned detection and attribution analyses generally focus on the single variable-based temperature extremes from the ETCCDI indices. These indices are defined by the daily maximum or minimum temperature, and thus temperature extremes only occur during daytime or nighttime, and simultaneous extremely hot days and nights are not accounted for. For example, the adverse effects of extremely hot days can be mitigated by subsequent cool nights, and extremely hot nights can trigger trouble with human thermoregulation even with relatively cool days (Gosling et al 2009, García-Herrera et al 2010). Compared with independent hot days or nights, combined daytime and nighttime hot events, namely compound hot events, can amplify the adverse effects on human society and ecosystems (Karl and Knight 1997). However, there are limited studies on the changes in compound hot events and the associated detection and attribution analyses. Chen and Zhai (2017) investigated the changes in hot extremes between 1961 and 2015 over China, based on station data. Ma and Yuan (2021) stated that global urbanization caused more summer compound hot extremes from 1971 to 2014 using station data, ERA-Interim reanalysis data and global artificial impervious area data. Increases in the frequency and intensity of compound hot events were found in the Northern Hemisphere from 1960 to 2012 utilizing HadGHCND observations, and greenhouse gas (GHG) forcing can be detected in the observed changes based on Coupled Model Intercomparison Project Phase 5 (CMIP5) climate models (Wang et al 2020). We would like to stress that whether human influence, especially from GHG forcing, can be detected at a smaller scale, such as over China, is not clear. Comparatively, CMIP6 models (Eyring et al 2016) provide more simulations, and the parameterization scheme and horizontal resolution have been improved, increasing the capability of models to a certain extent (Stouffer et al 2017). The Detection and Attribution Model Intercomparison Project is designed under the CMIP6 framework, and it can better estimate the contributions of ANT and NAT forcings to the observed climate changes at global and regional scales (Gillett et al 2016). Altogether, detection and attribution analyses of changes in compound hot events over China based on the CMIP6 models remain an open question.

According to these premises, this paper presents detection and attribution analyses on the changes in compound hot events over China from 1965 to 2014 utilizing the latest available CMIP6 models. We aim
to investigate the following: (a) What are the changes in hot extremes over China from gridded dataset CN05.1, and what are the comparisons between them with CMIP6 model simulations? (b) What is the human influence on the changes in compound hot events over China? This paper is organized as follows. Section 2 describes the data and methods. Section 3 provides the main results. The conclusions and discussion are given in section 4.

2. Data and methods

2.1. Data

The observed data are the daily maximum and minimum temperatures \( T_{\text{max}} \) and \( T_{\text{min}} \) from gridded dataset CN05.1 (Wu and Gao 2013). This dataset is produced by an interpolation method of the ‘anomaly approach’ based on 2416 stations in China, and it has a high horizontal resolution of 0.25° × 0.25°. We use daily maximum and minimum temperature data from CMIP6 simulations (Eyring et al. 2016) to estimate the responses of extreme temperature to the external forcings and the natural internal variability of the climate system. Given that some models have multiple ensemble members for some experiments, we apply all available ensembles for analysis. In this study, we utilize 44 simulations from 19 models under combined natural and anthropogenic (ALL) forcings, 27 simulations from eight models under NAT forcing, 15 simulations from eight models under ANT aerosol (AER) forcing and 28 simulations from ten models under GHG forcing. Our detection and attribution analyses are conducted over the period 1965–2014. Preindustrial control (CTL) simulations, in which the external forcing remains constant at the preindustrial level, are used to estimate the internal variability. The CTL simulations are divided into segments of 50 years, and a total of 92 segments from nine models are used. Table 1 lists the basic information about the simulations under individual models. As shown in Zhang et al. (2013), the responses to ALL and NAT forcings are assumed to be linearly additive, and the ANT response represents the difference between the responses to ALL and NAT forcings, that is ANT = ALL − NAT. Given the various horizontal resolutions of individual models, we interpolate all the model data into the same horizontal resolution as the observations.

2.2. Definition of hot extremes

An extremely hot day/night is considered to be when the \( T_{\text{max}}/T_{\text{min}} \) exceeds the 90th percentile (\( T_{\text{max}90}/T_{\text{min}90} \)) of its long-term counterparts. The 90th percentile of a specific calendar day is determined to be the 90th percentile of 15 d samples centered on this day (7 d before and after this specific day) from 1961 to 1990 (i.e. a total sample of 450 d), as defined in Chen and Zhai (2017). In this study, we focus on summertime (June–August) hot extremes. Specifically, we define three types of summertime hot events: an independent hot day—an extremely hot day without a following extremely hot night \( (T_{\text{max}} > T_{\text{max}90} \text{ and } T_{\text{min}} < T_{\text{min}90}) \); an independent hot night—an extremely hot night without a preceding extremely hot day \( (T_{\text{max}} < T_{\text{max}90} \text{ and } T_{\text{min}} > T_{\text{min}90}) \); and a compound hot event—an extremely hot day with a sequential extremely hot night \( (T_{\text{max}} > T_{\text{max}90} \text{ and } T_{\text{min}} > T_{\text{min}90}) \). Accordingly, the frequency for each type is measured by the number of days when \( T_{\text{max}}/T_{\text{min}} \) satisfies the corresponding constraints. The intensity is calculated as the exceedance of \( T_{\text{max}}/T_{\text{min}} \) above the respective threshold for an independent hot day/night; for a compound hot event, the intensity is considered to be the accumulated \( T_{\text{max}} \) and \( T_{\text{min}} \) exceeding their respective thresholds (Kuglitsch et al. 2010). Specifically, we first calculate separately the intensity of individual days on which the particular type of hot extremes occur, and then the annually averaged value is considered as the correspondingly annual intensity.

2.3. Detection and attribution method

Here, the optimal fingerprint method (Allen and Stott 2003) is utilized to regress the observations onto the multimodel mean signals, which is expressed as in the following regression equation (Ribes et al. 2013):

\[
y = \sum_{i=1}^{n} \beta_i x_i + \varepsilon
\]

where \( y \) indicates the observed values, \( x_i \) denotes the response to the \( i \)th individual forcing (including ALL, NAT, ANT, GHG and AER), \( \beta_i \) is the scaling factor corresponding to the \( i \)th forced signal as estimated by the total least squares method (Ribes et al. 2013), \( n \) represents the number of individual forcings and \( \varepsilon \) is the residual term, indicating the internal climate variability. Here, we use half of the segments of the CTL data to estimate the scaling factors, with the other half being used to estimate the 90% confidence intervals and test the residual consistency.

One-, two- and three-signal analyses are used in the detection and attribution analyses. We first conduct a one-signal analysis by regressing the observations onto multimodel mean responses to ALL forcing over China, which provides a simple overview to determine if the ALL signal can be detected in the observations. In the two-signal analysis, the observed results are simultaneously regressed onto the model-simulated responses to ANT and NAT forcings, determining whether these two signals can be detected in the observations and separated from each other. Here, the response to ANT forcing is referred to as the difference between multimodel mean responses to ALL and NAT forcings. Note that the difference between ALL and NAT responses relates to different models used for the estimation, whose effect is small overall (Dong et al. 2020). In the three-signal analysis,
the observations are simultaneously regressed onto NAT, GHG and AER signals. If the best estimate of the scaling factor and its 90% confidence interval are above zero, the corresponding signal is considered as to be detected in the observations. In those cases, if the 90% confidence interval for the scaling factor includes 1, it implies that the observed changes can be attributed to this forcing (Ribes et al 2013). When the best estimate of the scaling factor is <1, the simulated response needs to be diminished to match the observed values, and thus the model response overestimates the observed change.

In the detection and attribution analyses, conducting optimal fingerprinting typically requires the reduction of the spatial and temporal dimensions. To reduce the spatial dimension, we calculate regional averages over China onto one dimension for the detection analyses. In addition, we apply non-overlapping 5 year mean values to shorten the temporal dimension because the detection results are almost identical when using 3 or 5 year mean values (Yin et al 2017, Wang et al 2018b).

3. Results

3.1. Observed and modeled changes in hot extremes

Figure 1 shows the time series of annual anomalies in frequency and intensity for independent hot days, independent hot nights and compound hot events from observations and simulations (ALL, GHG, NAT and AER) over China from 1961 to 2014. For independent hot days, slight increases are seen in the observations and simulations for both frequency and intensity (figures 1(a) and (b)). In general, the observed changes in the frequency and intensity fall within the 90% ranges of the individual model-simulated responses to ALL and GHG forcings, and the multimodel mean responses to ALL and GHG forcings overestimate the observed changes. Specifically, the observed frequency and intensity exhibit slight upward trends of 0.4 d dec$^{-1}$ (where ‘dec’ is decade) and 0.03 °C dec$^{-1}$, respectively, which are lower than those of 0.5 d dec$^{-1}$ and 0.04 °C dec$^{-1}$ under ALL forcing and 0.7 d dec$^{-1}$ and 0.06 °C dec$^{-1}$ under GHG forcing (figure 2). In contrast, NAT forcing contributes little to the increases in both frequency and intensity, with trends of 0.03 d dec$^{-1}$ and 0.01 °C dec$^{-1}$; AER forcing leads to a decrease at a trend of −0.2 d dec$^{-1}$ for frequency and a negligible change for intensity. For independent hot nights, the observed intensity of compound hot events has the largest upward trend, with a magnitude of 0.1 °C dec$^{-1}$, and the frequency also increases obviously at a magnitude of 1.1 d dec$^{-1}$. The simulated responses to ALL and

| Model name         | Country or union | ALL | NAT | GHG | AER | CTL |
|--------------------|------------------|-----|-----|-----|-----|-----|
| AWI-CM-1-1-MR      | Germany          | 1   |     |     |     |     |
| ACCESS-ESM1-5      | Australia        |     | 1   | 1   | 1   |     |
| ACCESS-CM2         | Australia        |     |     |     |     |     |
| BCC-CSM2-MR        | China            | 1   | 3   | 3   | 3   |     |
| BCC-ESM1           | China            | 1   |     |     |     |     |
| CanESM5            | Canada           | 6   | 7   | 7   | 3   | 20  |
| CESM2              | USA              |     |     |     |     |     |
| CNRM-CM6-1h        | France           | 1   |     |     |     |     |
| CNRM-CM6-1         | France           | 4   | 3   | 2   |     |     |
| CNRM-ESM2-1        | France           | 5   |     |     |     |     |
| GFDL-CM4           | USA              | 1   |     |     |     |     |
| GFDL-ESM4          | USA              |     | 1   |     |     |     |
| GISS-E2-1G         | USA              | 1   |     |     |     |     |
| INM-CM4-8          | Russia           | 1   |     |     |     |     |
| INM-CM5-0          | Russia           | 2   |     |     |     |     |
| IPSL-CM6A-1-LR     | France           | 6   | 6   | 6   | 1   |     |
| MIROC6             | Japan            | 3   | 1   | 1   |     | 10  |
| MPI-ESM1-1-2-HAM   | Germany          | 1   |     |     |     |     |
| MPI-ESM1-2-LR      | Germany          | 2   |     |     |     |     |
| MRI-ESM2-0         | Japan            | 3   | 3   | 3   | 2   | 4   |
| NorESM2-LM         | Norway           | 3   | 3   | 3   |     | 10  |
| NorESM2-MM         | Norway           | 1   |     |     |     |     |
| Total (models)     | 22               | 44 (19) | 27 (8) | 28 (10) | 15 (8) | 92 (9) |
GHG forcings display greater upward trends than observational values, especially for GHG forcing. Specifically, the trends under ALL and GHG forcings are 1.3 d dec$^{-1}$ and 1.6 d dec$^{-1}$ for frequency and 0.1 °C dec$^{-1}$ and 0.2 °C dec$^{-1}$ for intensity, respectively. In contrast, NAT and AER forcings are not the major causes of the increased frequency and intensity of independent hot nights and compound hot events, and NAT and AER signals generally deviate from the ALL and GHG signals and observations after the mid-1990s.

For frequency, figure 3(a) shows a mixture of upward and downward trends of the observed independent hot days across China. Negative trends appear in part of northwestern China and most of eastern China, and positive trends occur in most of central China. The overall trend is positive. For independent hot nights, upward trends appear everywhere over China, and large values of more than 2.0 d dec$^{-1}$ are found in most of western and northeastern China (figure 3(b)). For compound hot events, upward trends are also seen almost everywhere, and the magnitudes are smaller than those for independent hot nights (figure 3(c)). Comparatively, the frequency trends are the strongest for independent hot nights, followed by compound hot events; those for independent hot days are the weakest.

The multimodel mean responses to ALL and GHG forcings have spatial patterns of frequency trends similar to the observations for independent hot nights and compound hot events, and those for independent hot days display somewhat different characteristics from the observations (figures 3(d)–(i)). The observed mixture of positive and negative trends of independent hot days are not reproduced in the ALL and GHG simulations, with upward trends appearing almost everywhere across China. For independent hot nights, stronger trends exist in the ALL and GHG simulations in southern China, and weaker trends are seen in northern China. For compound hot events, trend maps under ALL and GHG simulations agree with the observations, exhibiting larger magnitudes in western and southern China. Generally, GHG simulations exhibit stronger trends than ALL simulations for the three types of hot extremes. The NAT forcing simulations show a mixture of weakly positive and negative trends across China for the three types of hot extremes, and their spatial patterns exhibit inconsistency with the ALL and GHG simulations (figures 3(j)–(l)). The AER simulations show generally negative trends except for part of northern China.
Figure 2. Area-averaged observed and simulated trends of the (a) frequency (d dec$^{-1}$) and (b) intensity ($^\circ$C dec$^{-1}$) for independent hot days, independent hot nights and compound hot events over China from 1961 to 2014.

China but with smaller magnitudes than those under ALL and GHG forcings (figures 3(m)–(o)), indicating cooling effects of AERs on the three types of hot extremes.

Maps of the observed and simulated intensity trends of the three types of hot extremes are shown in figure 4. In the observations, both upward and downward trends of independent hot days are seen across China, with the strongest positive trends on the northeastern Tibetan Plateau (figure 4(a)). Negative trends are observed in the northern region of northwestern China and a small part of eastern China. For independent hot nights, positive trends are observed almost everywhere across China, with larger values in northern China (figure 4(b)). A similar spatial pattern holds for compound hot events, in which scattered negative trends occur in parts of eastern and northwestern China (figure 4(c)). The trends are the strongest for compound hot events.

The simulated intensity trends of the three types of hot extremes by the multimodel mean responses to ALL forcing share similar spatial patterns to those under GHG forcing (figures 4(d)–(i)). For independent hot days, both ALL and GHG simulations fail to reproduce the observed mixture of positive and negative trends across China, and stronger trends are simulated on the Tibetan Plateau. For independent hot nights, ALL and GHG simulations capture the overall positive trends across China, featuring larger magnitudes on the Tibetan Plateau. Comparatively, the simulated trends under ALL and GHG forcings are smaller than observational values, especially for northern China. Obvious intensifications of compound hot events across China are seen under ALL and GHG simulations, showing a general consistency with the observations, while the scattered negative trends are not reproduced. Similar to the frequency, GHG simulations exhibit stronger positive trends than those under ALL simulations, which may be relevant to the negative effect of other external forcings in the ALL experiment. For the three types of hot extremes, weakly positive trends under NAT simulations and a mixture of slightly upward and downward trends under AER simulations are obtained over China, and these two forcings contribute little to the increases in intensity.

3.2. Detection results for the changes in compound hot events
Figure 5 shows the best estimates of scaling factors and their 90% confidence intervals for the frequency and intensity of compound hot events using ALL simulations in one-signal detection analysis and ANT and NAT simulations in two-signal detection analysis. For one-signal detection, the best estimate of the scaling factor is 1.0 for both the frequency (90% confidence interval 0.7–1.4) and intensity (90% confidence interval 0.2–1.8) over China. In other words, the ALL
forcing is robustly detected in the observed changes in the frequency and intensity of compound hot events over China, as the 90% confidence intervals are above zero. As the best estimate of scaling factors for frequency and intensity is 1.0, there is a good agreement between ALL simulations and observations. Next, we investigate the changes in the frequency and intensity of compound hot events attributable to ALL forcing (figure 6). The attributable changes are calculated as the simulated linear trends multiplied by the corresponding best estimates of scaling factors and their 90% confidence intervals in the one-signal analysis. It is estimated that the ALL forcing has increased compound hot events by 7.5 d (90% range 4.9–10.1 d) for frequency and 0.7 °C (90% range 0.1–1.2 °C) for intensity over China from 1965 to 2014. These results are comparable to the observed changes of 7.0 d and 0.5 °C, respectively.

In the two-signal detection analysis, the best estimate of the scaling factor for ANT forcing is 1.0 (90% confidence interval 0.6–1.4) for frequency and 1.1 (90% confidence interval 0.2–2.0) for intensity. It is clear that the ANT signal can be detected over China, suggesting perceivable human influence on the increased frequency and intensity of compound hot events. Note that the best estimate of the scaling factor for ANT forcing is 1, implying that ANT simulations agree well with the observed changes in frequency; the value for intensity is slightly larger than 1, indicating that the simulated responses to ANT forcing need to be slightly amplified to match the observations. In contrast, the NAT signal cannot be detected for either the frequency or the intensity, as the 90% confidence intervals contain zero. Taken together, the observed changes in the frequency and intensity of compound hot events over China are largely due to human influence. The simulated responses to ANT forcing explain most of the observed changes in the frequency and intensity of compound hot events over China, and the estimated increases are 6.7 d (90% range 3.9–9.4 d) and 0.6 °C (90% range 0.1–1.1 °C), respectively. In contrast,
Figure 4. As in figure 3, but for the intensity.

Figure 5. Best estimates of the scaling factors and their 90% confidence intervals for (a) the frequency and (b) the intensity of compound hot events using the optimal fingerprint method from a one-signal (ALL) analysis and a two-signal analysis (ANT and NAT) over China from 1965 to 2014. In the one-signal analysis, the observations are regressed onto the model-simulated responses to ALL forcing. In the two-signal analysis, the observations are simultaneously regressed onto the model-simulated responses to ANT and NAT forcings. Linear least squares regression is used to estimate the trends for observations and simulations.
Figure 6. The attributable changes and their 90% confidence intervals for (a) the frequency and (b) the intensity of compound hot events. Attributable changes for ALL forcing are estimated by one-signal analysis, and those for ANT and NAT forcings are derived from two-signal analysis. The attributable changes are estimated by multiplying the linear least squares trends by the corresponding scaling factors.

Figure 7. Same as figure 5, but for GHG, AER and NAT forcings in three-signal analysis. Contributions of NAT forcing are relatively small, and the attributable changes are not estimated because the corresponding scaling factors are negative, which is not meaningful. Thus, we conclude that ANT forcing plays a dominant role in the observed changes in the frequency and intensity of compound hot events over China for the period 1965–2014.

Furthermore, we conduct three-signal detection analysis utilizing GHG, AER and NAT simulations (figure 7). It is indicated that a GHG signal can be detected for the observed increased frequency of compound hot events, with the best estimate of the scaling factor <1. Specifically, the best estimate of the scaling factor and its 90% confidence interval are 0.8 and 0.4–1.1. The AER and NAT signals cannot be detected, as the best estimate of the scaling factor is 0.9 (90% confidence interval −1.1 to 2.9) and 2.8 (90% confidence interval −0.3 to 5.9), respectively. For the intensity, the GHG signal cannot be detected as the 90% confidence interval contains zero. Note that when the GHG, ANTnoGHG (other ANT, including land-use change and AER emissions, as well as other factors) and NAT forcings are used in the three-signal detection analysis, the GHG signal can be detected. This may be related to the large model uncertainty in the AER response and the high colinearity between GHG and AER signals (Schurer et al 2018, DeSole et al 2019). The difference in the chosen time periods may also play a role, since the detectability may be higher for a slightly longer period for certain extreme temperature indices at regional scales (Hu et al 2020). Similarly, the NAT and AER signals cannot be detected. Quantitatively, it is estimated that GHG forcing has increased the frequency of compound hot events by 6.6 d (90% range 3.4–9.9 d) over China (figure 8). Overall, increases in the frequency and intensity induced by GHG forcing are larger than observational levels. As the NAT and AER forcings
cannot be detected, the attributable changes are not meaningful to compute.

4. Conclusions and discussion

Based on the latest experiments of CMIP6 models and the gridded dataset CN05.1, we first compared the observed changes in frequency and intensity of summer independent hot days, independent hot nights and compound hot events with simulations over China, and then used the optimal fingerprinting method to evaluate human influence on the frequency and intensity of compound hot events. Our primary conclusions are as follows.

(a) Remarkable increases are observed in the frequency and intensity of independent hot nights and compound hot events over China from 1961 to 2014, and slight increases are found in independent hot days. The simulated responses to ALL and GHG forcings generally match the observed spatial patterns of the frequency and intensity of independent hot nights and compound hot events but not of independent hot days. Overall, the magnitudes of increases in the frequency and intensity of the three types of hot extremes under GHG simulations are larger than those under ALL simulations. NAT and AER simulations exhibit weaker trends than their ALL and GHG counterparts.

(b) The combined ANT and NAT signal can be clearly detected in the observed changes in the frequency and intensity of compound hot events over China between 1965 and 2014. The two-signal analysis shows that ANT forcing can be detected, and the observed increases in the frequency and intensity of compound hot events over China could be mainly due to human influence. The three-signal analysis suggests the detectability of GHG forcing for the observed changes in the frequency of compound hot events, and the attributable changes are partially offset by the negative effects of ANT AER forcing. NAT and AER forcings cannot be detected.

We also applied the same method to the observed changes in independent hot days or nights. The ALL signal can be detected in the observed changes in their frequency and intensity. The best estimates of the scaling factors are 0.9 for both the frequency (90% confidence interval 0.1–1.8) and intensity (90% confidence interval 0.4–1.5) of independent hot days and 1.3 (90% confidence interval 1.1–1.4) and 1.1 (90% confidence interval 0.7–1.6) for those of independent hot nights. As such, there exists a detectable influence of ANT forcing on independent hot days and nights, particularly for the latter.

In this study, we realize that there are larger magnitudes of increases in nighttime extremes than in daytime extremes for both frequency and intensity. Taking independent hot days and nights into consideration together, slight increases in independent hot days can amplify the magnitude of extreme compound changes. With this expectation, we can identify the regions that are vulnerable to compound hot events and then develop more targeted strategies to adapt to and mitigate hot extremes. In addition, the specific ANT influences on climate extremes at global and regional scales, such as the urbanization effect and land-use change, need to be investigated in future work, which could help to provide a more comprehensive understanding of the causes of the changes in climate extremes.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://esgf-node.ipsl.upmc.fr/search/cmip6-ipsl/.
Acknowledgments

We sincerely thank the two anonymous reviewers for their insightful comments and suggestions to improve this manuscript. We acknowledge the climate modeling groups participating in the CMIP6 for producing and sharing their model outputs. This research was supported by the National Natural Science Foundation of China (41991284) and the Second Tibetan Plateau Scientific Expedition and Research Program (2019QZKK0101).

ORCID iDs

Xiaoxin Wang  https://orcid.org/0000-0001-6257-8877
Xianmei Lang  https://orcid.org/0000-0002-0022-9601
Dabang Jiang  https://orcid.org/0000-0003-0756-0169

References

Allen M R and Stott P A 2003 Estimating signal amplitudes in optimal fingerprinting, part I: theory Clim. Dyn. 21 477–91
Áström D O, Forsberg B, Ebi K L and Rocklöv J 2013 Attributing mortality from extreme temperatures to climate change in Stockholm, Sweden Nat. Clim. Change 3 1050–4
Chen X, Chen W, Su Q, Luo F, Sparrow S, Waldom D, Tian F, Dong B, Tett S F B and Lott F C 2019 Anthropogenic warming has substantially increased the likelihood of July 2017—like heat waves over central eastern China Bull. Am. Meteorol. Soc. 100 591–95
Chen Y and Zhai P 2017 Revisiting summertime hot extremes in China during 1961–2015: overlooked compound extremes and significant changes Geophys. Res. Lett. 44 5096–103
Christidis N, McCarthy M and Stott P A 2020 The increasing influence of extreme temperatures on health in the United Kingdom Nat. Commun. 11 3093
Christidis N and Stott P A 2016 Attribution analyses of temperature extremes using a set of 16 indices Geophys. Res. Lett. 32 L20716
DeSole T, Trenary L, Yan X Q and Tippett M K 2019 Confidence intervals in optimal fingerprinting Clim. Dyn. 52 4111–26
Donat M G et al 2013 Updated analyses of temperature and precipitation extreme indices since the beginning of the twentieth century: the HadEX2 dataset J. Geophys. Res. Atmos. 118 2098–118
Dong S, Sun Y, Aguilar E, Zhang X, Peterson T, Song L and Zhang Y 2018 Observed changes in temperature extremes over Asia and their attribution Clim. Dyn. 51 339–53
Dong S, Sun Y and Li C 2020 Detection of human influence on precipitation extremes in Asia J. Clim. 33 5293–304
Eyring V, Bony S, Meehl G A, Senior C A, Stevens B, Stouffer R J and Taylor K E 2016 Overview of the coupled model intercomparison project phase 6 (CMIP6) experimental design and organization Geosci. Model Dev. 9 1957–58
García-Herrera R, Díaz J, Trigo R, Luterbacher J and Fischer E 2010 A review of the European summer heat wave of 2003 Crit. Rev. Environ. Sci. Technol. 40 267–306
Gillett N P, Shioaga H, Funke B, Hegerl G and Tebaldi C 2016 The detection and attribution model intercomparison project (DAMIP v1.0) contribution to CMIP6 Geosci. Model Dev. 9 5685–97
Godling S N, Lowe J A, McGregor G R, Pelling M and Malamud B D 2009 Associations between elevated atmospheric temperature and human mortality: a critical review of the literature Clim. Change 92 299–341
Hegerl G C 2007 Understanding and attributing climate change Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (Cambridge: Cambridge University Press) pp 663–745
Hu T, Sun Y, Zhang X, Min S K and Kim Y H 2020 Human influence on frequency of temperature extremes Environ. Res. Lett. 15 064014
Imada Y, Siogama H, Takahashi C, Watanabe M, Mori M, Kamae Y and Maeda S 2018 Climate change increased the likelihood of the 2016 heat extremes in Asia Bull. Am. Meteorol. Soc. 98 597–101
IPCC 2012 Managing the risks of extreme events and disasters to advance climate change adaptation A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change ed C B Field et al (Cambridge: Cambridge University Press)
IPCC 2013 Summary for policymakers Climate Change 2013: The Physical Science Basis Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change ed T F Stocker et al (Cambridge: Cambridge University Press)
Karl T R and Knight R W 1997 The 1995 Chicago heat wave: how likely is a recurrence? Bull. Am. Meteorol. Soc. 78 1107–19
Kim Y-H, Min S-K, Zhang X, Zwiers F, Alexander L V, Donat M G and Tung Y 2016 Attribution of extreme temperature changes during 1951–2010 Clim. Dyn. 46 1769–82
Kuglis F G, Toreti A, Xoplaki E, Della-Marta P M, Zerefos C S, Türkeyl M and Luterbacher J 2010 Heat wave changes in the eastern Mediterranean since 1960 Geophys. Res. Lett. 37 L04802
Li H, Chen H, Wang H, Sun J and Ma J 2018 Can Barents Sea ice decline in spring enhance summer hot drought events over northeastern China? J. Clim. 31 4705–25
Liao W, Li D, Malyshov S, Shevlikova E, Zhang H and Liu X 2021 Amplified increases of compound hot extremes over urban land in China Geophys. Res. Lett. 48 e2020GL091252
Lu C, Sun Y, Wan H, Zhang X and Yin H 2016 Anthropogenic influence on the frequency of extreme temperature events in China Geophys. Res. Lett. 43 6511–8
Luca A D, Elía R, Bador M and Argüeso D 2020 Contribution of mean climate to hot temperature extremes for present and future climates Weather Clim. Extremes 28 100255
Ma F and Yuan X 2021 More persistent summer compound hot extremes caused by global urbanization Geophys. Res. Lett. 48 e2021GL093721
Ma S, Zhou T, Stone D A, Angelí O and Shiogama H 2017 Attribution of the July–August 2013 heat event in central and eastern China to anthropogenic greenhouse gas emissions Environ. Res. Lett. 12 054020
Min S K, Zhang X and Zwiers F W 2013 Multi-model detection and attribution of extreme temperature changes J. Clim. 26 7470–51
Mora C et al 2017 Global risk of deadly heat Nat. Clim. Change 7 501–6
Morak S, Hegerl G C and Christidis N 2013 Detectable changes in the frequency of temperature extremes J. Clim. 26 1561–74
Ren G and Zhou Y 2014 Urbanization effect on trends of extreme temperature indices of national stations over mainland China, 1961–2008 J. Clim. 27 2340–60
Ren L, Wang D, An N, Ding S, Yang K, Yu R, Freychet N, Tett S F B, Dong B and Lott F C 2020 Anthropogenic influences on the persistent night-time heat wave in summer 2018 over Northeast China Bull. Am. Meteorol. Soc. 101 583–8
Ribes A, Planton S and Terray L 2013 Application of regularised optimal fingerprinting to attribution. Part I: method, properties and idealised analysis Clim. Dyn. 41 2817–36
Schurer A, Hegerl G, Ribes A, Polson D, Morice C and Tett S 2018 Estimating the transient climate response from observed warming J. Clim. 31 8645–63
Sillmann J, Khari I, Zhang X, Zwiers F W and Bronaugh D 2013 Climate extremes indices in the CMIP5 multimodel ensemble: part 1. Model evaluation in the present climate J. Geophys. Res. Atmos. 118 1716–33
Song L, Sun Y, Dong S, Zhou B, Stott P A and Ren G 2015 Role of anthropogenic forcing in 2014 hot spring in northern China Bull. Am. Meteorol. Soc. 96 S111–5
Stott P A, Gillett N P, Hegerl G C, Karoly D J, Stone D A, Zhang X and Zwiers F 2010 Detection and attribution of climate change: a regional perspective WIREs Clim. Change 1 192–211
Stouffer R J, Eyring V, Meehl G A, Bony S, Senior C, Stevens B and 2017 CMIP5 scientific gaps and recommendations for CMIP6 Bull. Am. Meteorol. Soc. 98 95–105
Sui Y, Lang X and Jiang D 2018 Projected signals in climate extremes over China associated with a 2 °C global warming under two RCP scenarios Int. J. Climatol. 38 678–97
Sun Y, Hu T, Zhang X, Li C, Lu C, Ren G and Jiang Z 2019 Contribution of global warming and urbanization to changes in temperature extremes in Eastern China Geophys. Res. Lett. 46 11426–31
Sun Y, Zhang X, Zwiers F W, Song L, Wan H, Hu T, Yin H and Ren G 2014 Rapid increase in the risk of extreme summer heat in Eastern China Nat. Clim. Change 4 1082–5
Uhe P, Otto F E L, Haustein K, van Oldenborgh G J, King A D, Wallom D C H, Allen M R and Cullen H 2016 Comparison of methods: attributing the 2014 record European temperatures to human influences Geophys. Res. Lett. 43 8685–93
Wang H, Sun J, Chen H, Zhu Y, Zhang Y, Jiang D, Lang X, Fan K, Yu L and Yang S 2012 Extreme climate in China: facts, simulation and projection Meteorol. Z. 21 279–304
Wang J, Chen Y, Tett S F B, Yan Z, Zhai P, Feng J and Xia J 2020 Anthropogenically-driven increases in the risks of summertime compound hot extremes Nat. Commun. 11 528
Wang J, Tett S F B, Yan Z and Feng J 2018a Have human activities changed the frequencies of absolute extreme temperatures in eastern China? Environ. Res. Lett. 13 014012
Wang Y, Sun Y, Hu T, Qin D and Song L 2018b Attribution of temperature changes in western China Int. J. Climatol. 38 742–50
Wen Q, Zhang X, Xu Y and Wang B 2013 Detecting human influence on extreme temperatures in China Geophys. Res. Lett. 40 1171–6
Wu J and Gao X 2013 A gridded daily observation dataset over China region and comparison with the other datasets Chin. J. Geophys. Chin. Ed. 56 1102–11
Xu Y, Zhou B, Wu J, Han Z, Zhang Y and Wu J 2017 Asian climate change under 1.5 to 4 °C warming targets Adv. Clim. Chang Res. 8 99–107
Yin H and Sun Y 2018 Detection of anthropogenic influence on fixed threshold indices of extreme temperature J. Clim. 31 6341–52
Yin H, Sun Y and Donat M G 2019 Changes in temperature extremes on the Tibetan Plateau and their attribution Environ. Res. Lett. 14 124015
Yin H, Sun Y, Wan H, Zhang X and Lu C 2017 Detection of anthropogenic influence on the intensity of extreme temperature in China Int. J. Climatol. 37 1229–37
Zhang X, Wan H, Zwiers F W, Hegerl G C and Min S-K 2013 Attributing intensification of precipitation extremes to human influence Geophys. Res. Lett. 40 5252–7
Zhou B, Xu Y, Wu J, Dong S and Shi Y 2015 Changes in temperature and precipitation extreme indices over China: analysis of a high-resolution grid dataset Int. J. Climatol. 36 1051–66
Zwiers F W, Zhang X and Feng Y 2011 Anthropogenic influence on long return period daily temperature extremes at regional scales J. Clim. 24 881–92