Anthropogenic influence on extreme temperatures in China based on CMIP6 models

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Abstract

With rapid warming since the mid-20th century, China has experienced remarkable changes in the extreme temperatures. We use the updated observational data and the newest generation of climate models from Coupled Model Intercomparison Project Phase 6 (CMIP6) to investigate the relative contribution from different external forcing to the temperature extremes. We find that both intensity and frequency indices of extreme temperature experience continuous warming during 1951–2018. More intense and more frequent warm extremes and less intense and less frequent cold extremes are observed in most regions. An exception is a warming slowdown in the intensity of the coldest extremes since the late 1990s in northeast China. These observed changes are generally well reproduced by CMIP6 climate models, especially for the warm days and nights. Detection analyses based on an optimal fingerprinting method show that anthropogenic forcing (ANT) is the main driver for these changes, with cold extremes less detectability than warm extremes. Three-signal detections show that both greenhouse gas (GHG) and anthropogenic aerosols (AA) influences can be detected and separated in most warm extreme indices but not in the cold extremes, while the natural forcing influence is negligible for most indices. GHG forcing plays a dominant role, accounting for about 1.6 (1.1–2) times of observed warming in changes of most indices, while the AA offset about 35% (10–60%) of GHG induced warming for warm extremes. Anthropogenic factors including land use and ozone may have a very small positive contribution to the extreme temperatures.

Keywords
anthropogenic aerosol, anthropogenic forcing, CMIP6 models, detection and attribution, GHG, temperature extremes

1 | INTRODUCTION

As global mean temperature rises, the warm temperature extremes have increased and the cold extremes have decreased since the mid-20th century in most of global land areas (Alexander et al., 2006; Alexander, 2016; Dunn et al., 2020). China has experienced similar changes, witnessing clear increase in intensity, frequency and duration...
of warm extremes and decrease in cold extremes in most areas, especially after the mid-1990s (Zhou et al., 2016; Xie et al., 2020; China Meteorological Administration, 2019). The large changes are observed mainly in high-latitudes and high-mountain areas, including the Tibetan Plateau (Yin et al., 2019; You et al., 2020). The number of heat wave days with daily maximum temperature above 35°C has also increased, accompanied with earlier start and later end of heat wave season (Sun et al., 2018a). These changes have exerted serious impacts on economy, human health and other sectors in China (Gu et al., 2016; Xia et al., 2017; Chen et al., 2020; Shen et al., 2020). With the increase of greenhouse gas emissions in the future, the warming of extreme temperature will be very likely to continue into the future (Zhou et al., 2014; Hu and Sun, 2019; Li et al., 2019).

To explain external forcing reasons behind these changes, previous studies have found clear human influence on observed changes in extreme temperatures (Christidis et al., 2005; Bindoff et al., 2013). At global scale, the IPCC has concluded that human activities have very likely contributed to the changes in the frequency and intensity of extreme temperatures in most global land areas since the second half of the 20th century (Bindoff et al., 2013). A few new studies using the CMIP6 models further show that the warming is mainly caused by the greenhouse gases (GHG) at global and continental scales, which is partially offset by the cooling effects of anthropogenic aerosols (AA) (Hu et al., 2020; Seong et al., 2021). Hu et al. (2020) found continued warming after 2010 and the detected effect of AA over the globe and continents including Asia, Europe, North and South America in 1951–2018. At regional or national scale such as China, some studies have found that human influence is the main driver for observed changes in the intensity, frequency and duration of extreme temperature since the mid-20th century based on CMIP5 models (Wen et al., 2013; Sun et al., 2014; Lu et al., 2016; Yin et al., 2017; Dong et al., 2018; Sun et al., 2018b). The contribution from the anthropogenic forcing explains most of the observed changes in extreme temperatures, especially in the warm extremes. However, these studies do not separate the contribution from the GHG, aerosols and other forcings because of the limitation of available model experiments in CMIP5 models. The urbanization heat island effect is also found to play an important role in observed warming of extreme temperature, mainly in the changes of nighttime extremes, though the magnitude of urbanization effects still shows a large uncertainty (Ren and Zhou, 2014; Sun et al., 2019).

More recently, studies on changes and causes of extreme temperature have been extended to 2018 along with an updated observational data HadEX3 (Dunn et al., 2020) and a new incarnation of Coupled Model Intercomparison Project (CMIP6; Eyring et al., 2016). Dunn et al. (2020) found that this new observational dataset shows consistent changes in the extreme temperature with ongoing global warming. The changes in the indices derived from minimum temperature are greater than those from the maximum temperatures. On the other hand, individual forcing simulations from the CMIP6 Detection and Attribution Model Intercomparison Project (DAMIP, Gillett et al., 2016) have been released recently, including historical simulations with GHG, AA, natural forcings and so on. These simulations with updated climate forcings provide a good opportunity to investigate the relative contribution from different external forcings in attribution studies. Furthermore, the DAMIP experiments which have extended the simulation period from 2012 in CMIP5 to 2020 will support better understanding of climate forcings up to the latest decade in the early 21st century, such as the period of reduced warming (Watanabe et al., 2014).

Clearly, previous studies show a dominant role of the anthropogenic forcing in the extreme temperature changes at globe and in China. However, the relative contribution from GHG and aerosols to extreme temperature changes in China has not been investigated because the CMIP5 generally lack the separate aerosol experiments. A separate study focusing on the attribution of extreme temperature at national level is necessary for the climate change policy making in China. It is also unknown if the new generation of climate models (CMIP6) shows the similar detection results compared with the CMIP5. The article will thus be aimed to address these relevant issues, with a focus on recent warming features with extended observational data and on the quantification of contribution from different anthropogenic forcings including GHGs, aerosols and other anthropogenic factors. The article is structured as follows: Section 2 introduces the observational and model data and the detection and attribution method. Section 3 shows the results from the newly updated observational and model data, followed by the detection and attribution analyses conducted based on an optimal fingerprinting method. Section 4 summarizes the results.

## 2 DATA AND METHODS

A set of extreme temperature indices defined by the Expert Team on Climate Change Detection and Indices (ETCCDI) (Zhang et al., 2011, Table 1) are used to describe the changes in intensity and frequency of extreme temperatures. They include annual maxima and minima of daily maximum and minimum temperatures (TX, TN), and the warm and cold days and nights (TX90p, TN90p, TX10p and TN10p). These indices are calculated using the RCLimDex/FCLimdex software package that is available at http://etccdi.pacificclimate.org/software.shtml (Zhang et al., 2011).
2.1 | Observational data

We use a homogenized daily dataset at 2419 stations in China provided by China National Meteorological Information Center (Cao et al., 2016, http://data.cma.cn). With these daily data, the extreme temperature indices are first calculated at each station and then the anomalies are estimated relative to the 1961–1990 mean. A station is retained if 70% of the data during 1951–2018 and 3 years of data during 2016–2018 are available. This standard makes 2,367 stations retained across China. All these station anomalies are then averaged onto grid boxes of 1.25° (latitude) × 1.875° (longitude) resolution, which is consistent with the grid resolution used in HadEX3. The changes in regional mean of China, eastern China (east of 105°E, EC) and western China (west of 105°E, WC) are investigated by using the area-weighting method. The linear trends for each region are calculated by a non-parametric method (Sen, 1968; Zhang et al., 2000) instead of the least squares estimate as it is more suitable for the extreme temperature indices (Wan et al., 2019). The 5% level is used to define the statistically significant trend in this article.

2.2 | Model data

The daily data from CMIP6 simulations (Eyring et al., 2016) are used to calculate extreme temperature indices, including the experiments driven by historical all (ALL), historical GHG, historical AA and historical natural (NAT) forcings (Table 2). In total there are 25 historical simulations from five models available that have

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**Table 1** Definitions of the ETCCDI extreme temperature indices used

| Index | Name     | Definition                                      | Category | Units |
|-------|----------|-------------------------------------------------|----------|-------|
| TXx   | Max $T_{max}$ | Annual maximum value of daily maximum temperature | Intensity | °C    |
| TNx   | Max $T_{min}$ | Annual maximum value of daily minimum temperature | Intensity | °C    |
| TXn   | Min $T_{max}$ | Annual minimum value of daily maximum temperature | Intensity | °C    |
| TNn   | Min $T_{min}$ | Annual minimum value of daily minimum temperature | Intensity | °C    |
| TX90p | Warm days  | Annual percentage of days when daily maximum temperature >90th percentile | Frequency | %     |
| TN90p | Warm nights | Annual percentage of days when daily minimum temperature >90th percentile | Frequency | %     |
| TX10p | Cold days  | Annual percentage of days when daily maximum temperature <10th percentile | Frequency | %     |
| TN10p | Cold nights | Annual percentage of days when daily minimum temperature <10th percentile | Frequency | %     |

**Table 2** List of multimodel simulations used in this study. Numbers represent the ALL, SSP2-4.5, GHG, NAT and AA simulation ensemble sizes or the number of 68-year chunks for the CTL simulations

| Model       | ALL | SSP2-4.5 | GHG | NAT | AA | CTL |
|-------------|-----|----------|-----|-----|----|-----|
| 1. CanESM5  | 10  | 10       | 10  | 10  | 10 | 11  |
| 2. CNRM-CM6-1 | 7   |          |     |     |    |     |
| 3. CNRM-ESM2-1 | 7   |          |     |     |    |     |
| 4. EC-Earth3 | 7   |          |     |     |    |     |
| 5. EC-Earth3-Veg | 7   |          |     |     |    |     |
| 6. GFDL-CM4  | 7   |          |     |     |    |     |
| 7. GFDL-ESM4  | 7   |          |     |     |    |     |
| 8. HadGEM3-GC31-LL | 4 | 4 | 4 | 4 | 4 | 7 |
| 9. INM-CM4-8  | 7   |          |     |     |    |     |
| 10. IPSL-CM6A-LR | 5 | 5 | 5 | 5 | 5 | 17 |
| 11. MIROC-ES2L | 7   |          |     |     |    |     |
| 12. MIROC6    | 7   |          |     |     |    |     |
| 13. MPI-ESM1-2-HR | 7   |          |     |     |    |     |
| 14. MRI-ESM2-0 | 3 | 3 | 3 | 3 | 3 | 2 |
| 15. NorESM2-LM | 3 | 3 | 3 | 3 | 3 | 4 |
| 16. UKESM1-0-LL | 2   |          |     |     |    |     |
| SUM (models) | 25 (5) | 25 (5) | 25 (5) | 25 (5) | 25 (5) | 113 (16) |
same number of runs for ALL, GHG, NAT and AA experiments. The future projections under the SSP2-4.5 scenario during the period of 2015–2018 are used to extend the ALL simulations till 2018, as the ALL simulations generally end in 2014. A total of 113 runs from 16 models for the preindustrial control (CTL) experiments are also used in the study to estimate the internal variability.

All the 8 extreme temperature indices are calculated at native grids of the models and then interpolated onto the resolution of 1.25 × 1.875° that is consistent with the observational gridded data. The model data are masked by the available observed indices to replicate the consistent spatial and temporal coverage with observations as closely as possible. The area-weighted regional average anomalies (relative to 1961–1990 averages) are computed using the same procedure as those for observation in China, EC and WC.

The observed and simulated changes are averaged over space to meet the requirement of the method that all the data should follow a Normal (Gaussian) distribution. The simulated indices are further computed as multi-model ensemble means (MEMs) under different external forcings. Then all the observed and simulated time series are computed into non-overlapping 5-year mean series during 1951–2018 to reduce temporal variability. Because of the data limitation, the last point in the series only has 3 years.

2.3 Detection method

To assess the relative contributions of specific external forcing or combinations of several external forcings to the changes in extreme temperature, a regularized optimal fingerprint method (Allen and Stott, 2003; Ribes et al., 2013) is applied. This analysis assume that the observed change consists of a linear combination of externally forced signals plus internal variability, which generally holds for large-scale variables (Hegerl and Zwiers, 2011). The additive assumption has also been found valid for large-scale temperature change (Gillett et al., 2004; Shiogama et al., 2013). The observation \( y \) is regressed as a sum of scaled model-simulated signal \( X \) plus the internal climate variability \( \varepsilon \), that is, \( y = (X - \nu) \beta + \varepsilon \). \( \beta \) is the regression coefficient (namely, scaling factor), which adjusts the signal to best match the observation. \( \nu \) is the noise in the modelled response due to the internal variability. Whether the simulated internal variability is comparable to the internal variability of the observation is checked by conducting a residual consistency test. A signal is estimated to be detectable when the confidence interval of its corresponding scaling factor lies completely above zero. A scaling factor that is greater than unity demonstrates underestimation of the signal to the specific forcing by the models; conversely, one that is less than unity means overestimation. Consequently, when the confidence interval for \( \beta \) is above zero and includes one, it is suggested that the model-simulated fingerprint patterns are able to represent the observation with the expected amplitude, indicating an attribution claim.

The single-, two- and three-signal analyses are performed in this article. We conduct a single-signal analysis to detect the simulated responses to the ALL forcing (ALL signal). As the ALL forcing is a combination of anthropogenic forcing (ANT) and natural external forcing (NAT), we also conduct a two-signal analysis of the ANT (\( \text{ANT} = \text{ALL} - \text{NAT} \)) and NAT signals to further determine whether the ANT signal could be separated from the NAT signal. Besides, we used two methods to conduct three-signal analyses. The first one considers joint influence from GHG, AA and NAT, while the second one jointly detects influence from GHG, OANT (=\( \text{ALL-GHG-NAT} \)) and NAT. The difference of these two methods is the AA and OANT are separately treated in the detection analyses. The OANT signal is the response to other anthropogenic forcing agents including aerosols, ozone and land use change, estimated as \( \text{ALL-GHG-NAT} \). By applying these two methods, we can test if other anthropogenic factors can also be detected against the internal variability.

3 RESULTS

3.1 Observed and model simulated trends

Figure 1 illustrates observed spatial patterns of long-term trends in China over 1951–2012 and 1951–2018. For the intensity indices, the warmest extremes (TXx and TNx) have been strengthened in most areas at rates of 0–0.3°C per decade and the coldest extremes (TXn and TNn) have been significantly weakened since the early 1950s at rates of 0.2–0.6°C per decade. The changes in the coldest extremes are larger than those in the warmest extremes and are statistically significant in most regions, as there is a faster increase in minimum temperature extremes than maximum temperature extremes, which is consistent with previous studies (Dunn et al., 2020). The largest increases are observed in northern China, above 0.5°C per decade and significant at a 5% significance level, while a cooling is seen in the eastern part of China for TXx and TNx. The cooling areas are also seen in the previous studies by Zhou et al. (2016) using a high-resolution gridding data (CN05) during 1961–2010 and Yin et al. (2017) using same data but during a shorter period.
of 1958–2012. In comparison with the trends between two time periods, most of the warming during 1951–2018 is more obvious than those during 1951–2012 and regions with significant increasing trends have extended, while the cooling areas for the warm extremes in EC have shrunk and weakened during 1951–2018. We also note
that the coldest extremes (mostly in winter) show slight strengthening, which is also reflected in the time series of TXn and TNn (see Figure 3c,d).

For the frequency indices, the warm days and nights (TX90p and TN90p) have increased about 0.5–3% per decade and the cold days and nights (TX10p and TN10p) have decreased about 0.2–2.5% per decade across China. The remarkable changes are observed in western and northeastern China, especially for the significant increase of warm nights (TN90p) at rates above 3% per decade. A small area of decreasing trends is also seen in the eastern part of China for warm days (TX90p), which is consistent with the cooling in the intensity of the warmest temperature (TXx). Recalling previous studies, this cooling area is not found in the studies by Lu et al. (2016) who used a sparse horizontal resolution of 5° × 5°. This small cooling area is also not shown in the results for the same period by using the HadEX3 (not shown). This indicates that the spatial resolution and the available number of stations for the data could affect our findings about climate change at small regional scale area. For the extended period of 1951–2018, there are generally more warm extremes and less cold extremes than the period of 1951–2012, indicating a continued and more significant warming after 2012. But the cold nights also show slight increase in northeastern China, which corresponds to the increased intensity of the coldest extremes.

It is clear that the changes in extreme temperature show a continuous warming feature in the past decade. The shrinking cooling area in the eastern part of China can be found in a denser gridded data, which reminds us to pay attention to the data resolution even for the analysis of temperature related variables. Further comparison of two observational datasets based on HadEX3 (Figure 3, grey dashed lines) and China 2,419 stations (Figure 3, black solid lines) show that the averaged time series in China are roughly consistent, but there exist some differences when the region becomes smaller, such as the intensity indices of the coldest extremes in WC. There are slightly more increases in regional means of TXn and TNn after the year around 2010 in HadEX3 than those in 2419 station data (Figure 3c,d). The increase based on China station data is quite flat since the late 1990s, especially in WC. The disagreement may mainly stem from different station networks and coverage and gridding methods (Dunn et al., 2020). The frequency indices from the HadEX3 agree well with the observation. This suggests that the spatial coverage of HadEX3 may be sufficient to represent the spatial and temporal variations of frequency indices but miss some detailed information of intensity indices in the data sparse region.

Figure 2 shows the model simulated long-term trends from the median of CMIP6 MEM. The ALL simulations reasonably reproduce the long-term trends of the intensity and frequency indices in China, with small bias in representing the magnitudes of the indices changes but more homogeneous spatial pattern. There is a general agreement on warming trends among the models under ALL and GHG forcings all over China, and on cooling trends under AA and OANT forcings in most regions of China. The models produce diverse responses to the NAT forcing. For the intensity indices, the MEM slightly overestimates (about 0.1% per decade) the observed changes in the warmest extremes (TXx and TNx) and fails to replicate the cooling trends in the eastern part of China. The models show the same signs for trends in almost all the grids within China for TXx and TNx, indicating a good consistency among the models and so the robustness of the changes. The changes in the coldest extremes (TXn and TNn) are generally underestimated by the MEM, which is about 0.1–0.4° lower than the observed trends across China. The GHG simulations are spatially similar to the ALL but have larger increasing rates, indicating a dominant role of GHG forcing. The AA results show the cooling effects, which offset about one third (one tenth–six tenths) of the large warming induced by the GHG emissions. The OANT simulations, though dominated by aerosols, show some differences with the AA results. The most obvious difference is seen in northern China for the intensity indices. There is a clear cooling response to AA forcing but this could not be reflected in the OANT simulations, indicating the possible contribution from other factors such as the land use to the changes in these indices. For the frequency indices, the ALL experiments also show a good performance in simulating their changes, with the differences in the ranges of −0.2 to 0.2% per decade from the observation. The models reasonably reproduce the rapid warming of warm nights (TN90p) compared with other indices. The weak warming of TX90p in EC is also captured. The model responses to the GHG and AA show opposite effects with a larger response from GHG as those for the intensity indices. The responses to the OANT forcing are dominated by decreasing/increasing trends for warm/cold days and nights, but still with relatively weak increasing/increasing trends scattered over the western and northeastern parts. For all the indices, the NAT forcing only shows very small effects ranging from −0.05 to 0.05°C per decade for the intensity indices and approximately from −0.2 to 0.2% per decade for the frequency indices, respectively.

3.2 Temporal changes

The 5-year average anomaly series of the extreme temperature indices and their trends are shown in Figure 3. For the intensity indices (Figures 3a–d), the warmest
Extremes (TXx and TNx) have been strengthened since the mid-20th century and show a rapid increase since the mid-1990s. The coldest extremes (TXn and TNn) fluctuated before the early 1980s and then rapidly increased to a quite large value. The warming slowed down for the coldest extremes after the late 1990s and stayed in a quite flat phase, which evolved further to a slight reduction after the late 2000s in EC. When the trends of the coldest extremes are compared between the periods 1951–1990 and 1990–2018 (figures not shown), it shows that the
positive trends during 1951–1990 have turned to negative over the northern part of China (approximately north of 40°E) for the latter period, especially in northeast China.

This warming slowdown is also found in the previous studies (e.g., Sillmann et al., 2014; Yin et al., 2017) and has been linked to the regional winter cooling during the
global warming hiatus period (Sillmann et al., 2014). Some studies found a more pronounced winter cooling occurred in China at the period of 1998–2012 (Li et al., 2015a; 2015b), and lasted for recent decade (Chen and Zhai, 2017). The suggested reasons include possible changes in the ocean, aerosols, solar radiations and rapid Arctic sea ice decline (Meehl et al., 2013; England et al., 2014; Santer et al., 2014; Chripko et al., 2021).

The model simulated 5-year series under ALL forcing basically capture the long-term warming features in intensity indices. The simulated and observed warmest indices show a good agreement, with the observed trends lying within the 5th–95th percentile range of the simulated trends. For the coldest extremes, the models could not reproduce the fluctuation in observations and underestimate the remarkable warming since the 1980s, as well as the decelerated warming since the late 1990s. This recent warming slowdown is also unable to be reproduced by the CMIP5 models (Sillmann et al., 2014).

On the other hand, the GHG and ANT results show continuous warming features for the intensity indices, reflecting the possible influence from the natural internal variability (Meehl et al., 2013; England et al., 2014). Both AA and NAT forcings exert much smaller influence than the GHG and do not illustrate clear fluctuations around the 1990s, indicating that this warming slowdown may not be caused by anthropogenic and natural aerosols. The AA response even shows slight recovery in recent years that reflects the decreased emission of AA (Stevens et al., 2017; Fiedler et al., 2019), which is also seen in changes of OANT response. For the NAT experiments, after the CMIP6 fixed the volcanic forcing, the NAT influence is negligible that has been found having a small positive contribution in the CMIP5 models (Yin et al., 2017).

For the regional trends, it is clear that the positive trends of GHG, ANT and ALL simulations have similar magnitudes during 1951–2018 in China, EC and WC, which is slightly higher for TXx and TNx and much lower for TXn and TNn as compared with those of the observations. The OANT and AA show negative trends, with the magnitudes higher in AA simulations.

For the frequency indices (Figures 3e–h), the increase in warm days and nights and decrease in cold days and nights become clear since the 1980s and strengthened after the mid-1990s. The changes in WC are slightly larger than those in EC. The warm and cold nights (TN90p and TN10p) show larger changes as compared with the daytime indices. Under the ALL forcing, the model simulated frequency indices are fairly in good agreement with observations though slightly underestimate recent warming. The warm days and nights (TX90p and TN90p) are better represented by the CMIP6 models than other indices. The differences between observed and simulated trends mainly occur in EC since the 1990s. As in those for the intensity indices, the largest trends are seen in the GHG experiments and the weak opposite trends are found in the AA and OANT results. The NAT trends are too small (close to zero) to provide a reasonable result.

### 3.3 Single- and two-signal detections

Figure 4 shows the best estimates of scaling factors and their 90% confidence intervals for single- and two-signal detections. The ALL and ANT signals can be detected for all the indices, with the residual consistency test passed except TX90p for two-signal detections. The confidence intervals of scaling factors for frequency indices are generally narrower than those for the intensity indices, indicating a better consistency between the models and observations for the frequency indices. For intensity indices, the scaling factors for ALL and ANT are smaller or close to unity for the warmest extremes (TXx and TNx) while they are greater than unity for the coldest extremes. This indicates a slight overestimate of models for TXx, a good agreement between models and observation for TNx, and an underestimate for the coldest extremes, which is consistent with previous studies (Wen et al., 2013; Yin et al., 2017) and the above analyses. For the frequency indices, the best estimates of the scaling factors are quite close to unity for the warm days and nights, but they are slightly larger than unity for the cold nights. This suggests model’s good performance in reproducing the warm extremes and an underestimate of models for the cold nights. A few studies show that the urbanization heat island effects can reconcile the difference between the model simulated and observed nighttime extremes (Sun et al., 2019) and contribute about one third of warming to these indices. We speculate that the model imperfect ability in reproducing some key physical processes may also be important reason. For EC and WC, the detection results are quite similar to those for China. The only difference is seen for the detection of TNx and TNn in EC, which shows a quite large confidence interval with the value greater than unity. The large variation of these two indices (see Figure 3c,d) may be a reason that affects the detection results of the coldest extreme in this region, thus lending a support about the influence of internal variability on the coldest extremes. The NAT signals cannot be detected for the majority of the indices except a few indices in WC. The residual consistency test is generally passed except TX90p, which may be due to too small variability in model simulations.
Compared with previous results based on CMIP5 during a shorter period (Lu et al., 2016; Yin et al., 2017), our study confirms the dominant role of anthropogenic forcing in the extreme temperature changes. However, for the winter extremes, recent changes in TXn and TNn may reflect the influence of external natural forcing (Santer et al., 2014) and climate internal variability (Meehl et al., 2013; England et al., 2014) such as rapid Arctic sea ice decline (Chripko et al., 2021).

### 3.4 Three-signal detections

Two methods are used to conduct three signal detections. For the first one, three factors including GHG, AA and NAT are regressed with observations (Figure 5), while for the second one, GHG, OANT (ALL–GHG–NAT) and NAT are used (Figure 6).

In Figure 5, a general impression is that the GHG can be detected in most indices, while the GHG and AA can be separately detected only in warm extremes, but not in cold extremes. For the intensity indices, both GHG and AA signals can be simultaneously detected in the warmest days and nights in China, WC and EC. This suggests that both influences from GHG and AA signals can be found for the warm extremes against the internal variability when three forcing factors are considered. The NAT signals can only be robustly detected for TNx in China and WC. The residual consistency tests are passed in all the cases. For the frequency indices, the GHG, AA and NAT signals can be detected and separated from each other only for TX90p in WC. GHG signal can be detected for most frequency indices except TX10p in EC. NAT can be detected in some warm extremes but generally with large uncertainty intervals. The residual consistency tests failed for TX90p in WC, due to too low variability in model simulation and thus the confidence interval of the scaling factor may be too narrow for the detection to be valid.

Figure 6 shows the results based on the three signals of GHG, OANT and NAT. The detections are similar to Figure 5, generally with three signals detected and separated only for the intensity indices of the warmest extremes. For other indices, the GHG is still the dominant factor. Looking at the best estimates of scaling factors for OANT (Figure 6) and AA (Figure 5), they show some differences. For TXx, the best estimate of scaling factors for both GHG and AA are larger than unity, while they are slightly less than unity for GHG and close to unity for OANT. This indicates that anthropogenic factors, other than GHGs and AA, including the land use and ozone, also play roles in the change the extreme temperatures, but their contribution is generally small, which can be further seen in Figures 7 and 8.

### 3.5 Attributable changes

Figures 7 and 8 show the linear trends of the eight indices and their attributable changes to external forcing over...
China, EC and WC. Attributable changes are computed when the best estimate of a scaling factor is not below zero. During 1951–2018, the changes of indices in China are 1.01, 1.55, 2.04 and 3.33°C for TXx, TNx, TXn and TNn, respectively, and 7.34, 15.44, −5.15 and −10.42% for TX90p, TN90p, TX10p and TN10p, respectively. For all the indices, the ALL forcing signal explains most of observed changes, indicating the dominant role of external forcing. Two sub-national regions are marked by similar changes, with more warming in intensity indices and larger changes in frequency indices in WC.

For the intensity indices, GHG makes a large positive contribution which is offset by the AA cooling effects, while the NAT forcing effects are negligible. The GHG-induced changes explain more than 200% changes in EC and are slightly larger than other two regions, indicating a larger response of extreme temperature to GHG in EC. The AA responses offset a half and a third of the GHG induced changes in TXx and TNx, respectively. Similar results are found for warm extremes in other two regions. For the frequency indices, the GHG is still the major contributor while the AA contribution seems smaller compared with the intensity indices. GHG signal explains more than 110% of the frequency indices changes in most cases while the AA forcing signal offsets parts (from about 1/10 in TN90p up to about 1/3 in TX90p) of warming induced by the GHG forcing. The attributable changes from NAT are tiny as compared to those from the anthropogenic forcings. Taken TX90p in

![Figure 6](http://example.com/fig6.png)

**Figure 6** Same as Figure 5 but for the results from the threesignal analyses of GHG, OANT (estimated from ALL–GHG–NAT) and NAT.

![Figure 7](http://example.com/fig7.png)

**Figure 7** Trends in the observations (OBS) and that attributable to the ALL, GHG, AA and NAT forcings in the extreme temperature indices in 1951–2018. The attributable trend is estimated by multiplying the linear least squares trends in the relevant signal time series by the corresponding scaling factor. The attributable trend is shown only when the best estimate of corresponding scaling factor is greater than zero. Black whiskers mark 5–95% uncertainty ranges.
WC as an example, the amounts of warming attributable to the GHG, AA and NAT forcing are 14.3% (90% confidence interval: 10.0 to 18.2%), −6.2% (−9.6 to −2.4%) and 0.3% (0.1 to 0.5%), respectively. These sum up to 8.4%, almost equal to the observed change of 8.5%. Generally, a combination of the GHG- and AA-induced responses explains about 85 to 105% of the observed changes. The OANT signal (Figure 8) on average has a weaker cooling effect than the AA forcing signal (Figure 7). The differences suggest that even the OANT forcing signal is dominated by aerosols, the response to ozone changes and land use changes may have a positive contribution to the extreme temperature changes. We reshuffle the noise used in the three signal detections and found this conclusion is quite robust when different sets of noise are used. We thus speculate that anthropogenic factors such as ozone and land use change may induce a small positive warming for the extreme temperature changes.

4 | CONCLUSIONS

We use an extended observational data and the newest generation of CMIP6 models to investigate human influence on the extreme temperature changes during 1951–2018. The updated observations show that China has experienced continuous warming in most regions but witnessed a slowdown of warming in the intensity of coldest extremes after the late 1990s. The reasons behind these changes are investigated from a viewpoint of external forcing by applying an optimal fingerprinting method. The CMIP6 models well reproduce the observed changes in the warmest extremes (TXx and TNx) and the frequency indices, but underestimate the observed weakening of the coldest extremes (TXn and TNn). Both ALL and ANT signals can be detected in China, EC and WC, which is like previous studies. The three-signal detections, allowing a clear separation of different external forcings, suggests that the GHG and AA forcing signals can be detected and separated for warm extremes in most cases, while the cold extremes are mainly affected by the GHG forcing. Other anthropogenic factors can only be detected and separated for the intensity indices of the warmest extremes. The NAT signal can be detected in several cases but generally shows a large confidence interval.

Changes separately attributable to GHG, AA and NAT confirm that during 1951–2018, most of the observed warming in the intensity and frequency indices over China, WC and EC are attributed to the combined effect of anthropogenic forcing. This effect is mainly dominated by the warming from the GHG emission, accounted for about 1.6 (1.1–2) times of the observed changes in the selected indices. The GHG warming is partially offset, about 35% (10–60%), by the cooling effects from AAs for warm extremes. The OANT forcing show weaker cooling impacts than the AA forcing, which only
offset about 27% (6–49%) of the GHG-induced warming. Anthropogenic factors other than the GHG and AA forcings, including the land use and ozone, may make a small positive contribution to the extreme temperature changes. The slight difference of regional response to the GHG and AA can be seen between EC and WC, but is not significant for most indices. More studies are still needed to further clarify the roles from different factors, especially for the winter extremes.

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