Changes in Temperature Seasonality in China: Human Influences and Internal Variability

CHENG QIAN

Key Laboratory of Regional Climate-Environment for Temperate East Asia, Institute of Atmospheric Physics, Chinese Academy of Sciences, and University of Chinese Academy of Sciences, Beijing, China

XUEBIN ZHANG

Climate Research Division, Environment and Climate Change Canada, Toronto, Ontario, Canada

(Manuscript received 29 January 2019, in final form 20 June 2019)

ABSTRACT

Temperature seasonality, the difference between summer and winter temperatures in mid–high latitudes, is an important component of the climate. Whether humans have had detectable influences on changing surface temperature seasonality at scales smaller than the subcontinental scale, where humans are directly impacted, is not clear. In this study, the first detection and attribution analysis of changes in temperature seasonality in China has been carried out. Detection and attribution of both summer and winter temperatures were also conducted, with careful consideration of observational uncertainty and the inconsistency between observation and model simulations induced by the long coastline and country border in China. The results show that the response to external forcings is robustly detectable in the spatiotemporal pattern of weakening seasonality and in that of warming winter temperature, although models may have underestimated the observed changes. The response to external forcings is detectable and consistent with the observed change in summer temperature averaged over China. Human influences are detectable in changes in seasonality and summer and winter temperatures, most robustly in winter, and these influences can be separated from those of natural forcing when averaged over China. The recent increase in summer temperature was found to be due to external forcings, and the warming hiatus in winter temperature from 1998 to 2013 was due to a statistically significant cooling trend induced by internal variability. These results will give insights into the understanding of the warming hiatus in China, as well as the hot summers and cold winters in recent years.

1. Introduction

The annual cycle is the dominant component for many climate variables outside the tropics. The annual cycle of surface temperature is extremely large, accounting for up to more than 90% of the total variance in mid–high-latitude land areas (e.g., Thomson 1995; Qian et al. 2011; Qian and Zhang 2015). Changes in the amplitude of the annual cycle (also known as seasonality or the annual range) of land surface temperature have been reported and are gaining increasing interest from instrumental research (Thomson 1995; Mann and Park 1996; Wallace and Osborn 2002; Braganza et al. 2003; Jones et al. 2003; Stine et al. 2009; Qian et al. 2011; Drost and Karoly 2012; Stine and Huybers 2012; Qian and Zhang 2015; Cornes et al. 2017), tree-ring reconstruction (Duan et al. 2017), and

future projections (Dwyer et al. 2012; Yettella and England 2018). Changes in temperature seasonality are regarded as an important indicator of global climate change (Braganza et al. 2003), can affect the estimation of climate trends and variability (Qian et al. 2011), and have been suggested to be important in paleoclimatology (e.g., Andreasson and Schmitz 2000; Jones et al. 2003).

A distinct feature in observational data is that this seasonality is weakening in Northern Hemispheric mid–high latitudes, except near the Mediterranean region, where it has been strengthening since the 1950s (Stine et al. 2009; Qian and Zhang 2015). Human influence on the weakening in the temperature seasonality in the Northern Hemisphere from 1950 to 2005 has been detected, particularly in the high latitudes (50°–70°N) and East Asia, and the overall spatiotemporal pattern of phase 5 of the Coupled Model Intercomparison Project (CMIP5) model-simulated response to external and

Corresponding author: Cheng Qian, qianch@tea.ac.cn

DOI: 10.1175/JCLI-D-19-0081.1

© 2019 American Meteorological Society. For information regarding reuse of this content and general copyright information, consult the [AMS Copyright Policy](https://www.ametsoc.org/PUBSReuseLicenses) (www.ametsoc.org/PUBSReuseLicenses).

anthropogenic forcings is consistent with the observed changes as revealed through the optimal fingerprinting technique (Qian and Zhang 2015). To date, however, no optimal fingerprinting detection study has been performed with respect to the changing temperature seasonality of regions with a spatial scale smaller than that of the subcontinent, such as a particular country. Therefore, whether humans have had detectable influences at this scale is unclear. Detection and attribution at the regional scale, where humans are directly vulnerable to climate change, is more practical but also much more difficult than on the global scale because of a smaller signal-to-noise ratio (which makes the signal more difficult to detect) and the lower reliability of model-simulated internal variability as well as the response to forcings (Bindoff et al. 2013).

China is one of the ideal countries for studying human influences on changes in temperature seasonality, since it is located in the midlatitude temperate zone, where the annual cycle dominates the variance of the temperature record and a significant linear decrease in its temperature seasonality of 4.6% for the period 1961–2007 has been identified (Qian et al. 2011). China is also one of the largest carbon dioxide emitting countries. Human influences on China's average annual mean temperature since 1950 have been detected by the optimal fingerprinting approach (Zhang et al. 2006; Xu et al. 2015; Sun et al. 2016; Zhao et al. 2016).

Changes in temperature seasonality manifest as differing warming rates between summer and winter temperatures. For example, when winter mean temperature increased more quickly than summer mean temperature in northern high latitudes (50° – 70° N) and East Asia from 1950 to 2005, the seasonality weakened (Qian and Zhang, 2015). However, Cohen et al. (2012) noted that from 1987 to 2010 global temperatures experienced significant warming trends for all seasons except winter, during which cooling trends manifested across large regions of eastern North America and northern Eurasia. They suggested that the global warming hiatus (or “slowdown”) in the last decade or so is a seasonal phenomenon that is largely associated with anomalously cold Northern Hemisphere winter land surface temperatures, and this was later confirmed by Li et al. (2015a). They analyzed five datasets that showed that the global mean temperature warming hiatus between 1998 and 2012 was strongly influenced by a pronounced Northern Hemisphere midlatitude winter cooling trend.

China is located in the midlatitudes and the warming hiatus in winter temperature in China is also reflected in the analysis periods 1993–2007 (Qian et al. 2011), 1998–2012 (Li et al. 2015b), and 1998–2013 (Duan and Xiao 2015; Chen and Zhai 2017; Xie et al. 2017). By

arbitrarily configuring start and end years, Chen and Zhai (2017) revealed a “vantage hiatus period” in eastern China from 1998 to 2013 in daily minimum temperature, particularly during early to midwinter. Through analyzing changes in the temperature seasonality, Qian et al. (2011) suggested that the global dimming–brightening transition (Wild et al. 2005) in China associated with decadal change in surface solar radiation may help explain the decadal transition in summer and winter temperatures. By examining the variability of the temperature over different time scales, Xie et al. (2017) suggested that the recent warming hiatus was mainly associated with a downward change of decadal variability and tried to connect it to changes in atmospheric circulation. By employing the “circulation analog” method (Yiou et al. 2007), Chen and Zhai (2017) suggested that dynamic effects were fully responsible for occurrences of cold winters after 1998. Although the authors of these studies tried to explain the decadal transition in winter temperature, the roles of natural variability and human influence in the winter warming hiatus in China's average temperature after 1998 are still not clear, because surface solar radiation and atmospheric circulation may both be affected by natural variability and human influences in the Anthropocene. For example, Gillett and Fyfe (2013) found a significant strengthening of the northern annular mode in response to increasing greenhouse gases in the CMIP5 ensemble. Therefore, we need to take advantage of detection and attribution analysis.

The present study aims to carry out the first detection and attribution analysis of changes in the temperature seasonality in China. The result will also give us insights for understanding the role of human influences and natural variability in changes in summer and winter temperatures, the winter warming hiatus in China, and related hot summers and cold winters in the last decade or so. We will also introduce a method to deal with the long coastline and country border in China, and thus to make observations and model simulations as comparable as possible.

The remainder of the paper is organized as follows. Section 2 describes the observational and model-simulated data and the method to process and analyze these data, including the method to deal with the long coastline in China. Section 3 presents the observed and model-simulated changes in temperature seasonality and summer and winter mean temperatures, as well as the corresponding detection and attribution results, followed by an exploration of the role of external forcings and natural variability in these changes. After a brief discussion in section 4, we give a summary in section 5.

2. Data and methods

a. Data

1) OBSERVATIONS

Coastal grids in climate model simulations mix information from both the land and the ocean, while grids along national borders mix information from adjacent countries. Given that China has a long coastline and a long border that is shared with neighboring countries, a careful selection and treatment of datasets is necessary for a valid comparison of China-based land station observations with climate model simulations. To make observations and simulations as comparable as possible, we used the gridded monthly temperature anomalies data from HadCRUT4.6.0.0 (Morice et al. 2012) and the Climatic Research Unit gridded observational temperature dataset (CRUTEM4.6.0.0; Jones et al. 2012a,b) for the period 1950–2017. These data are on a $5^\circ \times 5^\circ$ latitude–longitude grid and are anomalies relative to the base period 1961–90 (Jones et al. 2012a,b). HadCRUT4.6.0.0 data have observations from both land and ocean, whereas CRUTEM4.6.0.0 data only have observations from land. Some coastal grids in China in the early period of HadCRUT4.6.0.0 have observations only from the ocean, which is also different from simulations. Therefore, we used CRUTEM4.6.0.0 data to mask the HadCRUT4.6.0.0 data first (referred to as the masked HadCRUT4.6.0.0 data herein), and thus the previously mentioned coastal grids in the early period are set as having missing values.

Station observations in China have inhomogeneity problems, especially because of the frequent relocation of stations. To take into account this problem, we also used the homogenized land-based temperature observations for the period 1960–2017 (Qian et al. 2019), updated from the China homogenized temperature (CHTM3.0) dataset (Li et al. 2016). This dataset was homogenized using the Multiple Analysis of Series for Homogenization method (Szentimrey 1999) and did not have missing values. It is referred to as CHTM4.0 in the following. There are 758 national Reference Climatic and Basic Meteorological Stations used in this study (Fig. 1), as in Qian et al. (2019). The results from this dataset were compared with those from the masked HadCRUT4.6.0.0 dataset. To determine the land portion for coastal grids, the National Centers for Environmental Prediction (NCEP)/National Oceanic and Atmospheric Administration (NOAA) land portion file at a resolution of $0.5^\circ \times 0.5^\circ$ was also used.

2) CLIMATE MODEL SIMULATIONS

Model simulations are monthly mean near-surface air temperatures from the CMIP5 archive, as used in Qian

FIG. 1. Map showing the China mask (blue grids) and demarcation of the four subregions used in this study and the corresponding abbreviations. The 758 available stations (green dots) in the CHTM4.0 dataset are also plotted. The number in each grid indicates the number of stations in the grid. Two red lines indicate 35°N and 105°E , which are used to divide the four regions.

and Zhang (2015, see their Table 1). We used historical simulations to estimate model-simulated temperature responses to six different external forcings; namely, natural and anthropogenic forcings combined (ALL), natural (NAT), anthropogenic (ANT), greenhouse gas (GHG), anthropogenic aerosol (AA), and land-use (LU) forcing only. We used preindustrial control simulations (piControl) to estimate natural internal climate variability in the detection and attribution analyses. Details of model information can be found in Qian and Zhang (2015). Since most of the CMIP5 historical simulations ended in 2005, the detection and attribution analyses were conducted for the period 1950–2005. To reconstruct the model-simulated response to historical ALL forcings to the latest years, simulations under the “medium” representative concentration pathways (RCP) scenario, that is, RCP4.5, for the period 2006–17 from available models, were used in this study.

b. Methods for the estimation of the annual cycle amplitude

Qian and Zhang (2015) showed that a simplified scheme using just half of the difference between the summer and winter mean temperature anomalies can well represent the change in the amplitude of the temperature annual cycle, since there is little difference in the decadal variability (after applying an 11-yr running mean) in the relevant anomaly time series from the simplified scheme and from the amplitude estimated

based on the annual cycle isolated by a temporally local and adaptive filter, and their trends are almost identical. Besides, the simplified scheme is much more computationally economical than the filter-based one in processing the large amount of model data, and we are interested in changes in the amplitude rather than the actual value of the amplitude. Therefore, we used the simplified scheme as in [Qian and Zhang \(2015\)](#) to compute the amplitude anomaly for the subsequent analysis and simply refer to the amplitude anomaly as “amplitude.” Summer is defined as June–August (JJA), while winter is defined as December–February (DJF). The formula is as follows:

$$\text{amplitude} = (T_{\text{JJA}} - T_{\text{DJF}})/2, \quad (1)$$

where T_{JJA} and T_{DJF} are temperature anomalies in the current JJA and the following DJF, respectively.

c. Data preprocessing

To make the observations and simulations as comparable as possible and to make station observations and HadCRUT4.6.0.0 data as comparable as possible, we masked the gridded HadCRUT4.6.0.0 data twice, first by CRUTEM4.6.0.0, as previously mentioned, and then by a China mask (see step (2) below), and then used them to mask simulations. Detailed steps are as follows:

- 1) Anomalies were calculated for each station and grid point of simulations by removing the relevant monthly mean values over the base period 1961–90, as was done in HadCRUT4.6.0.0. To some degree, this corrects the systematic bias in the model-simulated climatology. The reason for calculating anomalies first before regridding is to be consistent with CRUTEM4.6.0.0, as explained in [Qian and Zhang \(2015\)](#), since there are elevation differences among stations.
- 2) The anomalies from the station observations were gridded into the same $5^\circ \times 5^\circ$ grid boxes as HadCRUT4.6.0.0 by simply averaging the available station data within a $5^\circ \times 5^\circ$ grid box. For coastal grids, only those with a land portion larger than 60%, which is calculated based on the NCEP/NOAA land portion file, were included in this study in order to make station observations and HadCRUT4.6.0.0 as comparable as possible. This mask is referred to as the China mask ([Fig. 1](#)). The anomalies from simulations were also regridded to this common HadCRUT4.6.0.0 grid and then masked twice, as previously mentioned, to mimic availability of the CRUTEM4.6.0.0 data in China.
- 3) The detection and attribution analyses were conducted for China-averaged annual cycle amplitudes, and for summer temperature anomalies and winter temperature anomalies separately. The China-averaged variables were obtained by the grid-area weighted-average method, in which the cosine of the latitude of each $5^\circ \times 5^\circ$ grid box was used as the weight ([Jones and Hulme 1996](#)). While the temporal evolution of the average over the whole of China may provide a better signal-to-noise ratio, further analysis with finer spatial patterns improves confidence in the results of the detection. Therefore, we further computed area-weighted averages of the three variables over smaller land regions ([Fig. 1](#)) using the same method ([Jones and Hulme 1996](#)) as the China-averaged variables and conducted the detection analyses for (i) two space dimensions (2-zone hereafter), including northern China (north of 35°N) and southern China (south of 35°N); and (ii) four space dimensions (4-area hereafter), including northwestern China (NW), northeastern China (NE), southwestern China (SW) and southeastern China (SE), divided by 35°N and 105°E . The names of these four areas do not necessarily align well with geopolitical boundaries and are used for ease of reference. In such a way, the 2-zone and 4-area cases input increasingly finer spatial patterns in [Eq. \(2\)](#) than the China-averaged case.
- 4) The methods of generating the forced response and natural internal climate variability used in the detection and attribution analyses are the same as in [Qian and Zhang \(2015\)](#). Briefly, multimodel ensemble means (MMEs), obtained by first computing individual model ensemble means and then averaging across available models, both using the arithmetic mean, were used to represent a relevant forced response. This gives equal weights for different models and avoids models with larger numbers of ensemble members dominating the statistics of the MME. Besides, piControl simulations, which we have checked and found no apparent climate drifts, were divided into multiple nonoverlapping 56-yr segments, with the last segments discarded if shorter than 56 years. There were a total of 234 56-yr segments. Each segment was treated to mimic a 1950–2005 time series and processed using the above steps 1–3.

d. Methods for detection and attribution

We conducted detection and attribution analyses by using a total least squares–based optimal fingerprinting approach ([Allen and Stott 2003](#)) with a regularized

FIG. 2. China area-averaged annual anomalies of (a) amplitude of annual cycle and (b) summer mean temperature and winter mean temperature based on masked HadCRUT4.6.0.0 data for the period 1950–2016 and those based on CHTM4.0 for the period 1960–2016. Dashed lines indicate the corresponding linear trends based on the former dataset for the period 1950–2004, which is used in detection and attribution analysis. The statistical significances of these trends are given in parentheses.

covariance estimate (Ribes et al. 2009, 2013) on non-overlapping 5-yr mean values over large regions, as described in section 3c. This statistical model takes noise in the response patterns into consideration:

$$\mathbf{y} = \sum_{i=1}^m (x_i - \nu_i) \beta_i + \varepsilon, \quad (2)$$

where $\mathbf{y}$ is the spatiotemporal observation vector; x_i is the i th model-simulated response pattern from finite ensemble members and is, therefore, contained with sampling noise ν_i ; m is the number of signals, which in one-signal detection is 1 and in two-signal joint detection is 2, as conducted in this study; β_i is the i th scaling factor to be estimated; and ε is the noise in the observations.

We conducted one-signal detection for ALL, ANT, GHG, AA, and LU, respectively, and two-signal joint detection for ANT and NAT. We divided the 234 piControl segments into two halves for optimization and for uncertainty analysis, respectively. We applied temporal centering, achieved by removing the mean over the full period, to all the variables prior to input into Eq. (2); the formula takes into account noise in all variables proposed by Allen and Stott (2003) for computing confidence intervals of β_i , and a Monte Carlo–based residual consistency test scheme (Ribes et al. 2013) was used. If β_i is significantly greater than 0 (10% two-sided test), a signal is detected in the observations. Further, if its 90% confidence intervals include 1, the model-simulated response is consistent with the observed changes.

e. Reconstructions of model-simulated response to ALL forcings and internal variability

Since the model-simulated response may overestimate or underestimate the observations because of different

equilibrium climate sensitivities in different models (Flato et al. 2013), although the spatial and/or temporal pattern of the response is correct, the observationally constrained forced response is estimated here by multiplying the ALL forcings responses scaling factor obtained from our one-signal detection to best match the observed variations in the variable (Allen and Stott 2003). The difference between this reconstructed response to ALL forcings and the observations is then regarded as internal variability. This method is similar to that used in Frankcombe et al. (2015), except the scaling used here is based on the optimal fingerprinting approach, and is argued more reliable than those from the simple linear detrending or the removal of raw multimodel mean (Frankcombe et al. 2015). To calculate the relative contribution, we also estimated the attributable trend by the ordinary least squares trends of the relevant signal multiplying corresponding scaling factors.

3. Results

a. Comparison between HadCRUT4.6.0.0 and CHTM4.0

Figure 2a shows that China area-averaged anomalies of the amplitude of the annual cycle based on masked HadCRUT4.6.0.0 data are very close to those based on CHTM4.0 for the same period, 1960–2016, as are the anomalies of summer mean temperature and winter mean temperature (Fig. 2b). These results indicate that the masked HadCRUT4.6.0.0 dataset is suitable for the analysis in this study, although the number of stations in China used in the HadCRUT4.6.0.0 dataset is smaller than that in the CHTM4.0 dataset. Besides, the HadCRUT4.6.0.0 dataset includes ocean information

FIG. 3. Trends in the (a),(d) amplitude, (b),(e) summer mean temperature, and (c),(f) winter mean temperature in the (left) observations and (right) model-simulated responses under ALL forcings for the period 1950–2004. The two blue lines indicate 35°N and 105°E, as used in Fig. 1. Crosses in (a)–(c) represent linear trends that are statistically significant at the 5% level.

for coastal grids and information from neighboring countries for border grids, which is more consistent with the model simulations than the CHTM4.0 dataset. In addition, the former dataset is longer than the latter one. Therefore, we used the masked HadCRUT4.6.0.0 dataset for the observations in the subsequent analysis. Based on this dataset, we obtained the linear trends in the anomalies of amplitude, summer mean temperature and winter mean temperature for the period 1950–2004 (1950–2016) as $-0.15^{\circ}\text{C decade}^{-1}$ ($-0.089^{\circ}\text{C decade}^{-1}$), $0.10^{\circ}\text{C decade}^{-1}$ ($0.17^{\circ}\text{C decade}^{-1}$), and $0.39^{\circ}\text{C decade}^{-1}$ ($0.35^{\circ}\text{C decade}^{-1}$), respectively; these trends are statistically significant at the 1% level (5% level), 5% level (1% level), and 1% level (1% level), respectively. The trend was calculated using ordinary least squares fitting and the significance was assessed using the revised

Mann–Kendall test with a prewhitening approach that removes the first-order autocorrelation calculated through an iterative process proposed by Zhang et al. (2000) and refined by Wang and Swail (2001). The subsequent trend analyses were carried out in this way.

b. Spatial and temporal pattern of the observations and model-simulation responses

It should be noted that the number of available stations in China within the CRUTEM4.6.0.0 dataset is much larger than that within the CRUTEM4.2.0.0 dataset used in Qian and Zhang (2015) for the same period; thus, the spatial patterns in Fig. 3 differ noticeably compared with the counterparts in Fig. 2 of Qian and Zhang (2015) in terms of the China domain,

FIG. 4. The 5-yr mean anomalies of China-averaged (a),(d) amplitudes, (b),(e) summer mean temperature, and (c),(f) winter mean temperature in the observations (black line) and in the model-simulated responses to ALL (red line), NAT (blue line), GHG (magenta line), AA (green line), and LU (yellow line) forcing. The gray area marks the 5th–95th percentile range of simulated corresponding variables from 79 individual model runs under ALL forcing.

although the analysis periods and methods are exactly the same.

Figure 3a shows that the observed amplitude has a decreasing trend almost everywhere in China, statistically significant in the majority of northern and eastern China and with the magnitude basically larger in the north than in the south. This characteristic corresponds to a faster warming in winter than in summer (Figs. 3b,c) and a faster warming in the north than in the south in winter (Fig. 3c). The trend in summer has spatial differences, with parts of southeastern China having a cooling trend and statistically significant warming mostly in the northern border of China (Fig. 3b), whereas winter has warmed everywhere, statistically significant in the majority of northern China, parts of eastern China and southwestern China (Fig. 3c). The model-simulated response pattern under ALL forcings is somewhat similar to the observed changes, especially the decreasing amplitude (Fig. 3d), the warming summer (Fig. 3e) and stronger winter warming (Fig. 3f) in northern China. But, the magnitudes of the response are much weaker for the

amplitude and winter warming than those in the observation (Figs. 3a,d,c,f).

China-averaged temporal evolutions of the 5-yr mean anomaly of the three variables are shown in Fig. 4. Visual inspection reveals that the observed data generally lie in the 5th–95th percentile range of the CMIP5 simulations (Figs. 4a–c), implying that the current climate models have the capacity to roughly capture the observed changes, especially in summer mean temperature (Fig. 4b). Model-simulated responses are more consistent with the observations when the ANT forcing is included, although model-simulated responses under ALL forcings are smaller than the observations (Figs. 4a,c), except for the good agreement for summer mean temperature (Fig. 4b). The simulated amplitude is still much smaller than the observed changes even with the new version of CRUTEM data and excluding the ocean grids in this study compared with the East Asia case shown in Qian and Zhang (2015); this indicates that the underestimation in East Asia is primarily due not to observational uncertainty or land–sea difference but to the underestimation of warming in winter temperature

(Fig. 4c). For individual anthropogenic forcings, only GHG forcing causes a slight weakening seasonality; the effect of AA or LU forcing has no apparent trend (Fig. 4d). However, the effect of GHG and AA forcing is strong in summer mean temperature and winter mean temperature changes, with the response under GHG forcing stronger than the observed warming and canceled out partly by the cooling effect of the AA forcing for both seasons (Figs. 4e,f). LU forcing has a slight cooling effect on summer and winter mean temperatures (Figs. 4e,f). Then, the question that naturally follows is whether the influences of these forcing components can be detected. This question will be answered in the next section.

c. Detection and attribution

The results of one-signal detection for ALL, ANT, GHG, AA, and LU forcing, respectively, are shown in Fig. 5. The influence of AA or LU forcing cannot be detected; thus, it is not shown in Fig. 5. The results show that the response to ALL forcing is robustly detectable in the spatiotemporal pattern of amplitude and in that of winter mean temperature, although models may have underestimated the observed changes for one, two and four dimensions. The response to ALL forcing can be detected in summer mean temperature for one and two dimensions, and is consistent with the observed change, but not for four dimensions. If we only use the six models that conducted ANT simulations (ALL6) to do the detection analysis, the results are the same for summer and winter mean temperatures. The results of ANT forcing are also the same as ALL forcing for these two variables. For the amplitude, however, the response to ALL6 cannot be detected for the one-dimensional case, though the response to ANT forcing can be detected for the two- and four-dimensional cases and is consistent with the observed change for the four-dimensional case. As to the response to GHG forcing, it can be detected in summer mean temperature for the two- and four-dimensional cases but not for one dimension, suggesting that the GHG effect can be detected but not very robustly. In addition, model-simulated responses to GHG forcing in this season are larger than the observed changes, as scaling factors are smaller than unity, which is understandable considering the cooling effect of aerosol forcing. In contrast, GHG forcing can be robustly detected in the spatiotemporal pattern of winter mean temperature for the one-, two-, and four-dimensional cases and is consistent with the observed changes. The varying detection results among different signals or different spatial configurations of regions indicate the detection result becomes less robust at such a scale.

FIG. 5. Scaling factors and their 90% confidence intervals for (left) amplitudes, (center) summer mean temperature, and (right) winter mean temperature in China when the detection analysis is conducted with one (China), two (2-zone), and four (4-area) spatial dimensions. Only one signal is used in this detection analysis, including ALL (blue), ANT (red), GHG (magenta), and ALL simulations from the six models that conducted ANT simulations (ALL6; light blue). Scaling factors are not shown if residual consistency tests failed.

We further investigated the spatial pattern of the model-simulated response to the detectable ANT and GHG forcing (Fig. 6). Although the signal of GHG forcing is detected in summer and winter temperatures but not in the amplitude, we still show the response of the amplitude to GHG forcing in Fig. 6 for comparison. The response pattern to ANT forcing shows decreasing trends in the amplitude in most grids (Fig. 6a) and warming trends everywhere for both summer and winter mean temperatures (Figs. 6b,c), with stronger warming in the north than in the south for the winter case (Fig. 6c). These patterns resemble the observed changes (Figs. 3a–c). As to the response pattern to GHG forcing, northeastern and southwestern China show decreasing amplitudes in most grids, but trends in northwestern and southeastern China are not consistent with the observations (Figs. 6d and 3a); both summer and winter mean temperatures show warming trends everywhere (Figs. 6e,f) and stronger warming in the north than in the south in winter (Fig. 6f), but the magnitude in summer is stronger than that in the observation, especially in northwestern China (Figs. 6e and 3b), whereas it is weaker than the observations in the north in winter (Figs. 6f and 3c).

In an attempt to separate model-simulated responses to ANT and NAT forcings in the observations, we conducted two-signal joint detection analysis with these two signals. The models used in this analysis are the same six models that conducted ANT simulations. The result (Fig. 7) shows that the response to ANT forcing

FIG. 6. As in Fig. 3, but for (a)–(c) ANT and (d)–(f) GHG forcing.

may be separated from that to NAT forcing in a one-dimensional analysis for the amplitude, in both one- and two-dimensional analyses for summer mean temperature, and in the spatiotemporal pattern for winter mean temperature. In addition, the response to ANT forcing is underestimated for the amplitude and winter mean temperature but is consistent with the counterpart in the observations for summer mean temperature.

To calculate the relative contributions of the detectable forcings to the observed changes in China-averaged variables, we estimated the attributable trends (Fig. 8). According to the one-signal detection result, ALL forcings contributed approximately 66% (from -0.16 to $-0.05^{\circ}\text{C decade}^{-1}$) of the observed change in the amplitude, almost 100% (0.07° – $0.13^{\circ}\text{C decade}^{-1}$) in summer mean temperature, and 74% (0.20° – $0.37^{\circ}\text{C decade}^{-1}$) in winter mean temperature. According to the two-signal joint detection result with ANT and NAT forcing, ANT

forcing contributed approximately 142% (from -1.32° to $-0.10^{\circ}\text{C decade}^{-1}$) of the observed change in the amplitude, 107% (0.06° – $0.15^{\circ}\text{C decade}^{-1}$) in summer mean temperature, and almost 100% (0.27° – $0.53^{\circ}\text{C decade}^{-1}$) in winter mean temperature. The contribution from NAT forcing is relatively small for all three variables.

d. Reconstructions of forced responses and internal variability

We further extended the reconstructed forced response to external forcings and the corresponding internal variability to recent years (2006–16) to see their roles in recent decadal change (Fig. 9). Since separate reconstructions for winter and summer temperatures will provide better insight, and since the scaling factor of the amplitude is more uncertain than those of winter and summer temperatures, this analysis was not conducted for amplitude. The results suggest that the recent

FIG. 7. As in Fig. 5, but for the joint two-signal analyses, in which responses to ANT and NAT forcing (from the six models that conducted ANT simulations; NAT6) are used as predictors in Eq. (2). Only the scaling factors that have reasonable uncertainty bounds are shown.

increase in summer mean temperature is due to the external forcings (including the hiatus period, 1998–2013, for which the trend is $0.28^{\circ}\text{C decade}^{-1}$ and statistically insignificant in the observation, and that of the response to external forcings is $0.24^{\circ}\text{C decade}^{-1}$ and statistically significant at the 1% level), as is the temporary cooling in the 1950s and early 1960s (Fig. 9a). The trend of the response to internal variability during 1998–2013 is trivial ($0.04^{\circ}\text{C decade}^{-1}$), even taking into account the uncertainty of the scaling factor (up to $0.11^{\circ}\text{C decade}^{-1}$) (Fig. 9a). In contrast, the recent warming hiatus in observed winter mean temperature from 1998 to 2013 ($-0.58^{\circ}\text{C decade}^{-1}$, not significant) is due to the cooling trend ($-1.32^{\circ}\text{C decade}^{-1}$, significant at the 5% level) induced by internal variability, while the external forcings still drive the temperature toward an overall warming tendency over this period ($0.74^{\circ}\text{C decade}^{-1}$, significant at the 1% level) (Fig. 9b). Taking into account the uncertainty of the scaling factor, the conclusion remains the same, with the magnitude of the cooling trend induced by internal variability during 1998–2013 ranging from $-1.54^{\circ}\text{C decade}^{-1}$ (significant at the 5% level) to $-1.10^{\circ}\text{C decade}^{-1}$ (significant at the 5% level) (Fig. 9b). Besides, the warming hiatus after 1998 in winter mean temperature has not recovered even if the end year for the trend calculation is 2016 ($0.03^{\circ}\text{C decade}^{-1}$ for the period 1998–2016, not significant), and is seen as a platform also because of the cooling trend ($-0.81^{\circ}\text{C decade}^{-1}$, significant at the 10% level) induced by internal variability (Fig. 9b).

FIG. 8. Estimated contributions of ALL (red), ANT (magenta), and NAT (blue) forcings to observed changes (gray) in China-averaged (left) amplitude, (center) summer mean temperature, and (right) winter mean temperature during the 1950–2004 period. Colored bars show best estimates of the attributable trends with 90% confidence intervals.

4. Discussion

As explained in Qian and Zhang (2015), the amplitude is the difference between the summer and winter mean temperatures, and the signals that exist in both seasons are of the same sign (Figs. 6e,f); therefore, the difference between them would have a much-reduced magnitude. Additionally, the variability in the amplitude is also larger than that in both the summer and winter mean temperature. Consequently, the signal-to-noise ratio in the amplitude should be smaller, resulting in a less robust detection for the amplitude and a more uncertain (i.e., larger uncertainty bound) estimate of the scaling factor. This is clearly shown in Figs. 5 and 7.

The warming hiatus in winter temperature in China from 1998 to 2013, although not statistically significant, as revealed in this study, was found to be due to a statistically significant cooling trend induced by internal variability. This finding is similar to Imada et al. (2017), who suggested that the recent enhanced seasonal temperature contrast (increased summer temperature while decreased winter temperature) in Japan during 1999–2010 was mainly been induced by atmospheric anomalies responding to decadal La Niña-like conditions in the tropical Pacific. They analyzed the outputs of 100 ensemble simulations of historical and counterfactual nonwarming climate simulations conducted using a high-resolution atmospheric general circulation model (AGCM). In their counterfactual nonwarming climate simulation, negative anomalies in 500-hPa geopotential height occupied East Asia in cold seasons (their Fig. 7f) in association with decadal La Niña-like conditions

FIG. 9. Observed (black curves) and reconstructed (red curves) China area-averaged annual anomalies of (a) summer mean temperature and (b) winter mean temperature for forced responses during the 1950–2016 period. The former minus the latter indicates internal variability (green curves). Model-simulated responses to ALL forcings (blue curves) and the uncertainties of internal variability due to the uncertainty of the scaling factor (gray areas) are also plotted. See section 2e for details. Black, red, and green dashed lines represent the linear trend of the observation, that of the forced response, and that induced by internal variability for the period 1998–2013, respectively. The corresponding best estimates of the trend slopes are shown, with * (**) representing that the trend is statistically significant at the 5% (1%) level.

during 1999–2010. As reviewed in the introduction, a warming hiatus in winter temperature manifested across large regions of midlatitude Eurasia. Mori et al. (2014) showed that a warm Arctic and cold Eurasia pattern, a distinct intrinsic mode of atmospheric variability independent of Arctic Oscillation and representing temperature variations associated with the sea ice concentration (SIC) in the Barents–Kara Sea region, is associated with cold winter temperature anomalies in midlatitude East Asia, including northern and eastern China (their Figs. 2b,d). Mori et al. (2019) further analyzed seven state-of-the-art AGCMs driven by historical sea surface temperature and SIC data and found that all the models capture the observed structure of the forced surface temperature response to sea ice loss in the Barents–Kara Seas—including Eurasian cooling—but its magnitude is systematically underestimated. After correcting this underestimation, they concluded that approximately 44% of the central Eurasian cooling trend for 1995–2014 is attributable to sea ice loss in the Barents–Kara Seas. The detailed physical processes related to the internal variability that induced the warming hiatus in winter temperature in China deserve further study but are beyond the scope of this paper.

It should also be noted that the RCP scenarios in CMIP5 models focused on anthropogenic emissions and did not have observed volcanic and solar forcings for much of the period after 2000 (Folland et al. 2018). However, the sun has gone into a quieter phase since about 2004 (Schmidt et al. 2014); and barring a major volcanic eruption, RCP4.5 forcings are unlikely to diverge strongly from reality (see Box 9.2 of Flato et al.

2013). Nevertheless, the warming hiatus in China is at least not induced by human influences.

5. Summary

We carried out the first detection and attribution analysis of changes in temperature seasonality in China by the optimal fingerprinting approach. External forcings were robustly detected in the spatiotemporal pattern of changing seasonality, although the model-simulated response was weaker than observed. Anthropogenic forcing can also be detected in two dimensions and four dimensions, and the response to ANT forcing can be separated from that of the NAT forcing when averaged over China. Through detection and attribution analysis of both summer and winter mean temperatures, we found that the model-simulated responses to ALL and to ANT forcing in summer mean temperature can be detected and are consistent with the observation when averaged over China, the latter of which can be separated from that of NAT forcing, and that the model-simulated response to ALL and to ANT forcing in winter mean temperature can be robustly detected in the spatiotemporal pattern in China, the latter of which can be separated from that of NAT forcing, although the simulated magnitudes are all weaker than observed. Through adjustment of the response to external forcings, we found the recent increase in summer mean temperature was due to external forcings, and the warming hiatus in winter temperature from 1998 to 2013 was due to a statistically significant cooling trend induced by the internal variability overwhelming the warming trend induced by external

forcings. The situations for the period 1998–2016 are similar.

Acknowledgments. This study was jointly sponsored by the National Key R&D Program of China (Grant 2016YFA0600404 and 2018YFC1507701), the National Natural Science Foundation of China (Grant 41675093), the Youth Innovation Promotion Association of the Chinese Academy of Sciences (2016075), and the Jiangsu Collaborative Innovation Center for Climate Change. We acknowledge the three anonymous reviewers for their suggestions, which helped us to further improve the manuscript. We also acknowledge the Program for Climate Model Diagnosis and Intercomparison and the World Climate Research Programme's Working Group on Coupled Modelling for their roles in making the WCRP CMIP multimodel datasets available.

REFERENCES

- Allen, M. R., and P. A. Stott, 2003: Estimating signal amplitudes in optimal fingerprinting, part I: Theory. *Climate Dyn.*, **21**, 477–491, <https://doi.org/10.1007/s00382-003-0313-9>.
- Andreasson, F. P., and B. Schmitz, 2000: Temperature seasonality in the early middle Eocene North Atlantic region: Evidence from stable isotope profiles of marine gastropod shells. *Geol. Soc. Amer. Bull.*, **112**, 628–640, [https://doi.org/10.1130/0016-7606\(2000\)112<628:TSITEM>2.0.CO;2](https://doi.org/10.1130/0016-7606(2000)112<628:TSITEM>2.0.CO;2).
- Bindoff, N. L., and Coauthors, 2013: Detection and attribution of climate change: From global to regional. *Climate Change 2013: The Physical Science Basis*, T. F. Stocker et al., Eds., Cambridge University Press, 867–952.
- Braganza, K., D. J. Karoly, A. C. Hirst, P. Stott, R. J. Stouffer, and S. F. B. Tett, 2003: Simple indices of global climate variability and change. Part I: Variability and correlation structure. *Climate Dyn.*, **20**, 491–502, <https://doi.org/10.1007/s00382-002-0286-0>.
- Chen, Y., and P. Zhai, 2017: Persisting and strong warming hiatus over eastern China during the past two decades. *Environ. Res. Lett.*, **12**, 104010, <https://doi.org/10.1088/1748-9326/aa822b>.
- Cohen, J. L., J. C. Furtado, M. Barlow, V. A. Alexeev, and J. E. Cherry, 2012: Asymmetric seasonal temperature trends. *Geophys. Res. Lett.*, **39**, L04705, <https://doi.org/10.1029/2011GL050582>.
- Cornes, R., P. Jones, and C. Qian, 2017: Twentieth-century trends in the annual cycle of temperature across the Northern Hemisphere. *J. Climate*, **30**, 5755–5773, <https://doi.org/10.1175/JCLI-D-16-0315.1>.
- Drost, F., and D. Karoly, 2012: Evaluating global climate responses to different forcings using simple indices. *Geophys. Res. Lett.*, **39**, L16701, <https://doi.org/10.1029/2012GL052667>.
- Duan, A., and Z. Xiao, 2015: Does the climate warming hiatus exist over the Tibetan Plateau? *Sci. Rep.*, **5**, 13 711, <https://doi.org/10.1038/srep13711>.
- Duan, J., and Coauthors, 2017: Weakening of annual temperature cycle over the Tibetan Plateau since the 1870s. *Nat. Commun.*, **8**, 14 008, <https://doi.org/10.1038/ncomms14008>.
- Dwyer, J. G., M. Biasutti, and A. H. Sobel, 2012: Projected changes in the seasonal cycle of surface temperature. *J. Climate*, **25**, 6359–6374, <https://doi.org/10.1175/JCLI-D-11-00741.1>.
- Flato, G., and Coauthors, 2013: Evaluation of climate models. *Climate Change 2013: The Physical Science Basis*, T. F. Stocker et al., Eds., Cambridge University Press, Cambridge, 741–866.
- Folland, C. K., O. Boucher, A. Colman, and D. E. Parker, 2018: Causes of irregularities in trends of global mean surface temperature since the late 19th century. *Sci. Adv.*, **4**, eaao5297, <https://doi.org/10.1126/sciadv.aao5297>.
- Frankcombe, L. M., M. H. England, M. E. Mann, and B. A. Steinman, 2015: Separating internal variability from the externally forced climate response. *J. Climate*, **28**, 8184–8202, <https://doi.org/10.1175/JCLI-D-15-0069.1>.
- Gillett, N., and J. Fyfe, 2013: Annular mode changes in the CMIP5 simulations. *Geophys. Res. Lett.*, **40**, 1189–1193, <https://doi.org/10.1002/grl.50249>.
- Imada, Y., S. Maeda, M. Watanabe, H. Shiogama, R. Mizuta, M. Ishii, and M. Kimoto, 2017: Recent enhanced seasonal temperature contrast in Japan from large ensemble high-resolution climate simulations. *Atmosphere*, **8**, 57, <https://doi.org/10.3390/atmos8030057>.
- Jones, P. D., and M. Hulme, 1996: Calculating regional climatic time series for temperature and precipitation: Methods and illustrations. *Int. J. Climatol.*, **16**, 361–377, [https://doi.org/10.1002/\(SICI\)1097-0088\(199604\)16:4<361::AID-JOC53>3.0.CO;2-F](https://doi.org/10.1002/(SICI)1097-0088(199604)16:4<361::AID-JOC53>3.0.CO;2-F).
- , K. R. Briffa, and T. J. Osborn, 2003: Changes in the Northern Hemisphere annual cycle: Implications for paleoclimatology? *J. Geophys. Res.*, **108**, 4588, <https://doi.org/10.1029/2003JD003695>.
- , D. H. Lister, T. J. Osborn, C. Harpham, M. Salmon, and C. P. Morice, 2012a: Hemispheric and large-scale land-surface air temperature variations: An extensive revision and an update to 2010. *J. Geophys. Res.*, **117**, D05127, <https://doi.org/10.1029/2011JD017139>.
- , —, —, —, —, and —, 2012b: The CRUTEM4 dataset, version 4.2.0.0. Met Office Hadley Centre, accessed 2 September 2018, <http://www.cru.uea.ac.uk/cru/data/temperature/#datdow>.
- Li, C., B. Stevens, and J. Marotzke, 2015a: Eurasian winter cooling in the warming hiatus of 1998–2012. *Geophys. Res. Lett.*, **42**, 8131–8139, <https://doi.org/10.1002/2015GL065327>.
- Li, Q., S. Yang, W. Xu, X. L. Wang, P. Jones, D. Parker, L. Zhou, Y. Feng, and Y. Gao, 2015b: China experiencing the recent warming hiatus. *Geophys. Res. Lett.*, **42**, 889–898, <https://doi.org/10.1002/2014GL062773>.
- Li, Z., L. Cao, Y. Zhu, and Z. Yan, 2016: Comparison of two homogenized datasets of daily maximum/mean/minimum temperature in China during 1960–2013. *J. Meteor. Res.*, **30**, 53–66, <https://doi.org/10.1007/s13351-016-5054-x>.
- Mann, M. E., and J. Park, 1996: Greenhouse warming and changes in the seasonal cycle of temperature: Model versus observations. *Geophys. Res. Lett.*, **23**, 1111–1114, <https://doi.org/10.1029/96GL01066>.
- Mori, M., M. Watanabe, H. Shiogama, J. Inoue, and M. Kimoto, 2014: Robust Arctic sea-ice influence on the frequent Eurasian cold winters in past decades. *Nat. Geosci.*, **7**, 869–873, <https://doi.org/10.1038/ngeo2277>.
- , Y. Kosaka, M. Watanabe, H. Nakamura, and M. Kimoto, 2019: A reconciled estimate of the influence of Arctic sea-ice

- loss on recent Eurasian cooling. *Nat. Climate Change*, <https://doi.org/10.1038/s41558-018-0379-3>.
- Morice, C. P., J. J. Kennedy, N. A. Rayner, and P. D. Jones, 2012: Quantifying uncertainties in global and regional temperature change using an ensemble of observational estimates: The HadCRUT4 data set. *J. Geophys. Res.*, **117**, D08101, <https://doi.org/10.1029/2011JD017187>.
- Qian, C., and X. Zhang, 2015: Human influences on changes in the temperature seasonality in mid- to high-latitude land areas. *J. Climate*, **28**, 5908–5921, <https://doi.org/10.1175/JCLI-D-14-00821.1>.
- , C. Fu, and Z. Wu, 2011: Changes in the amplitude of the temperature annual cycle in China and their implication for climate change research. *J. Climate*, **24**, 5292–5302, <https://doi.org/10.1175/JCLI-D-11-00006.1>.
- , X. Zhang, and Z. Li, 2019: Linear trends in temperature extremes in China, with an emphasis on non-Gaussian and serially dependent characteristics. *Climate Dyn.*, **53**, 533–550, <https://doi.org/10.1007/s00382-018-4600-x>.
- Ribes, A., J.-M. Azais, and S. Planton, 2009: Adaptation of the optimal fingerprint method for climate change detection using a well-conditioned covariance matrix estimate. *Climate Dyn.*, **33**, 707–722, <https://doi.org/10.1007/s00382-009-0561-4>.
- , S. Planton, and L. Terray, 2013: Application of regularized optimal fingerprinting to attribution. Part I: Method, properties and idealised analysis. *Climate Dyn.*, **41**, 2817–2836, <https://doi.org/10.1007/s00382-013-1735-7>.
- Schmidt, G. A., D. T. Shindell, and K. Tsigaridis, 2014: Reconciling warming trends. *Nat. Geosci.*, **7**, 158–160, <https://doi.org/10.1038/ngeo2105>.
- Stine, A. R., and P. Huybers, 2012: Changes in the seasonal cycle of temperature and atmospheric circulation. *J. Climate*, **25**, 7362–7380, <https://doi.org/10.1175/JCLI-D-11-00470.1>.
- , —, and I. Y. Fung, 2009: Changes in the phase of the annual cycle of surface temperature. *Nature*, **457**, 435–440, <https://doi.org/10.1038/nature07675>.
- Sun, Y., X. Zhang, G. Ren, F. W. Zwiers, and T. Hu, 2016: Contribution of urbanization to warming in China. *Nat. Climate Change*, **6**, 706–709, <https://doi.org/10.1038/nclimate2956>.
- Szentimrey, T., 1999: Multiple Analysis of Series for Homogenization (MASH). *Proc. Second Seminar for Homogenization of Surface Climatological Data*, Budapest, Hungary, World Climate Data and Monitoring Programme 41, WMO/TD 962, 27–46.
- Thomson, D. J., 1995: The seasons, global temperature, and precession. *Science*, **268**, 59–68, <https://doi.org/10.1126/science.268.5207.59>.
- Wallace, C. J., and T. J. Osborn, 2002: Recent and future modulation of the annual cycle. *Climate Res.*, **22**, 1–11, <https://doi.org/10.3354/cr022001>.
- Wang, X. L., and V. R. Swail, 2001: Changes of extreme wave heights in Northern Hemisphere oceans and related atmospheric circulation regimes. *J. Climate*, **14**, 2204–2221, [https://doi.org/10.1175/1520-0442\(2001\)014<2204:COEWHI>2.0.CO;2](https://doi.org/10.1175/1520-0442(2001)014<2204:COEWHI>2.0.CO;2).
- Wild, M., and Coauthors, 2005: From dimming to brightening: Decadal changes in solar radiation at earth's surface. *Science*, **308**, 847–850, <https://doi.org/10.1126/science.1103215>.
- Xie, Y., J. Huang, and Y. Liu, 2017: From accelerated warming to warming hiatus in China. *Int. J. Climatol.*, **37**, 1758–1773, <https://doi.org/10.1002/joc.4809>.
- Xu, Y., X. J. Gao, Y. Shi, and B. T. Zhou, 2015: Detection and attribution analysis of annual mean temperature change in China. *Climate Res.*, **63**, 61–71, <https://doi.org/10.3354/cr01283>.
- Yettella, V., and M. R. England, 2018: The role of internal variability in twenty-first-century projections of the seasonal cycle of Northern Hemisphere surface temperature. *J. Geophys. Res. Atmos.*, **123**, 13 149–13 167, <https://doi.org/10.1029/2018JD029066>.
- Yiou, P., R. Vautard, P. Naveau, and C. Cassou, 2007: Inconsistency between atmospheric dynamics and temperatures during the exceptional 2006/2007 fall/winter and recent warming in Europe. *Geophys. Res. Lett.*, **34**, L21808, <https://doi.org/10.1029/2007GL031981>.
- Zhang, X., L. A. Vincent, W. D. Hogg, and A. Niitsoo, 2000: Temperature and precipitation trends in Canada during the 20th century. *Atmos.–Ocean*, **38**, 395–429, <https://doi.org/10.1080/07055900.2000.9649654>.
- , F. W. Zwiers, and P. A. Stott, 2006: Multimodel multisignal climate change detection at regional scale. *J. Climate*, **19**, 4294–4307, <https://doi.org/10.1175/JCLI3851.1>.
- Zhao, T. B., C. X. Li, and Z. Y. Zuo, 2016: Contributions of anthropogenic and external natural forcings to climate changes over China based on CMIP5 model simulations. *Sci. China Earth Sci.*, **59**, 503–517, <https://doi.org/10.1007/s11430-015-5207-2>.