Detecting human influence on the temperature changes in Central Asia

Dongdong Peng^{1,2,3} · Tianjun Zhou^{2,3,4} · Lixia Zhang² · Liwei Zou^{2,4}

Received: 2 October 2018 / Accepted: 6 May 2019 / Published online: 14 May 2019
© The Author(s) 2019

Abstract

The ecosystem and societal development in arid Central Asia are highly vulnerable to climate change. During the past five decades, significant warming occurs in Central Asia, but whether the influence of anthropogenic forcing is detectable remains unclear. Therefore, we employ the optimal fingerprinting method to address the question in this study. The observed annual mean temperature (°C) over Central Asia significantly increases by 1.33 from 1961 to 2005, which mainly concentrates in summer (0.90), autumn (1.22), and winter (2.48). The influence of anthropogenic forcing, particularly the greenhouse gases (GHG) forcing, on both the annual and seasonal significant warming trends are robustly detected. GHG increases the annual, summer, autumn, and winter mean temperature (°C) by 1.25 (0.52–2.00), 1.11 (0.32–1.92), 1.11 (0.40–1.83), and 2.50 (0.91–4.34), respectively. Attribution results demonstrate an underestimation (overestimation) of CMIP5 models in simulating the annual and winter (summer and autumn) historical warming trend in Central Asia, implying a potential bias of the future temperature projections reported in IPCC AR5. Thus, we adjust the projections based on the attributed scaling factors, showing that the projected annual, summer, autumn, and winter mean temperature would significantly increase at a rate (°C decade⁻¹) of 0.32 (0.16–0.49), 0.20 (0.06–0.35), 0.24 (0.10–0.38) and 0.58 (0.24–0.93) under RCP4.5, while 0.74 (0.36–1.12), 0.48 (0.14–0.84), 0.58 (0.25–0.91), and 1.25 (0.53–2.02) under RCP8.5, respectively, demonstrating large annual variation. To the end of twenty-first century, the annual (winter) mean temperature (°C) over Central Asia would increase by 7.00 (11.75) under RCP8.5, 0.85 (5.17) higher than the unadjusted results.

Keywords Detection and attribution · Central Asia · Optimal fingerprinting method · Future projection

1 Introduction

Far from ocean and lying on the north of Tibetan Plateau (Fig. 1a), Central Asia (35°–55°N, 50°–95°E) is one of the most arid regions with an annual precipitation amount less than 350 mm (Fig. 1b) and characterized by cool desert climate with sparse vegetation (shrubland and grassland) and

vast deserts (Huang et al. 2016a; Hu et al. 2017). Against the background of global warming, the warming rate in arid regions is much larger than that in humid regions, which results in greater threat in the vulnerable ecological system over Central Asia (Hu et al. 2014; Huang et al. 2016a, b, 2017). Meanwhile, Central Asia is a key connecting region bridging Asia to Europe owing to its geographical position. Studies of climate change over Central Asia are of great importance to the development of both local and global economy and society.

Central Asia has experienced a significant warming (about 0.15 °C decade⁻¹) during the past one hundred years, with an accelerating warming rate (about 0.33 °C decade⁻¹) in recent five decades which is much higher than the global land average (about 0.19 °C decade⁻¹) (Hu et al. 2014; Zhou et al. 2018; IPCC 2013). In Northwest China which is located at the eastern part of Central Asia, the winter warming rate is larger than the other seasons, and is associated with weakening winter Siberian High and increasing

✉ Tianjun Zhou
zhoujt@lasg.iap.ac.cn

¹ Institute of Tropical and Marine Meteorology, China Meteorological Administration, Guangzhou, China

² LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing 100029, China

³ University of Chinese Academy of Sciences, 100049, Beijing, China

⁴ CAS Center for Excellence in Tibetan Plateau Earth Sciences, Chinese Academy of Sciences (CAS), Beijing 100101, China

Fig. 1 The distribution of climatological mean **a** annual temperature (unit: °C) and **b** precipitation amount (unit: mm) over Asia during 1961–2005. Magenta lines indicate the Tibet Plateau (with an altitude higher than 3000 m). Black boxes indicate the region Central Asia (35°–55°N, 50°–95°E)

greenhouse gases concentrations (Li et al. 2012, 2013a; Bai et al. 2015). Meanwhile, the precipitation in Central Asia shows significant increasing trend during the past five decades, with the largest increasing trend in Northwest China (Shi et al. 2007; Chen et al. 2011; Zhao et al. 2014; Li et al. 2016; Hu et al. 2017). Consequently, results from rain gauge observations indicate that the climate over Northwest China shifts from warm and dry to warm and wet (Shi et al. 2007; Li et al. 2015, 2016, 2017b; Dong et al. 2018; Rodell et al. 2018).

The significant increasing precipitation in Northwest China is associated with the increased evaporation results from significant warming during the past half-century (Chen et al. 2011; Peng and Zhou 2017; Peng et al. 2018). Associated with the significant warming over Central Asia during the past five decades, the areas of dry-land expanded acceleratedly, temperature and precipitation extremes increased significantly, and the glacier in Tianshan Mountains retreated markedly (Deng et al. 2014; Chen et al. 2016; Huang et al. 2016a; Wang et al. 2017).

Detection and attribution studies based on model simulations provide a useful way in understanding the relative contribution of internal climate variability and different external forcings to the observed climate change. Meanwhile, attribution results can correct the overestimation (underestimation) of model simulations, providing more reasonable information of future projection (Allen et al. 2000; Wang et al. 2018). Results based on the detection and attribution studies conclude that “It is extremely likely that human influence has been the dominant cause of the observed warming since the mid-twentieth century” (IPCC 2013).

Although detection and attribution studies should be more difficult at a smaller region because of the lower ratio of signal to noise (Stott et al. 2010; Hegerl and Zwiers 2011), increasing evidence demonstrate human influence on the changes in regional mean and extreme temperature (Wen et al. 2013; Zhou et al. 2014; Sun et al. 2014, 2016a, b; Xu et al. 2015; Lu et al. 2016; Ma et al. 2017a; Yin et al. 2017; Wang et al. 2018). The observed increases in annual mean temperature (Xu et al. 2015; Sun et al. 2016b), intensity of extreme temperature (Wen et al. 2013; Yin et al. 2017), and frequency of extreme temperature (Lu et al. 2016) in China during the past half century are attributable to anthropogenic forcings. Besides, many studies show the evidence that human influence has significantly increased the occurrence chance of the extreme high temperature events in China (Zhou et al. 2014; Sun et al. 2014, 2016a; Song et al. 2015; Ma et al. 2017a).

Recently, anthropogenic influence on the observed annual warming during past 50 years has been detected for global arid region (Li et al. 2017a) and arid western China (Wang et al. 2018). However, less effort has been devoted to the detection and attribution of the annual and seasonal mean temperature changes in Central Asia. Thus in this study, we aim to conduct the detection and attribution studies on the observed changes in annual and seasonal mean temperature over Central Asia based on the optimal fingerprinting method. We show evidences that the observed annual and seasonal warming trends in Central Asia are attributable to the increased anthropogenic greenhouse gas and the annual temperature adjusted by the attributed scaling factors would increase at a higher rate during twenty-first century.

We organized the remainder of this paper as follows: The observed and model simulated datasets as well as the optimal fingerprinting method are introduced in Sect. 2. In Sect. 3, we firstly attribute the observed temperature changes using the model simulations driven with different external forcings, and then discuss the projected temperature changes based on the attribution results. Finally, the main results are concluded in Sect. 4.

Table 1 List of historical simulations of the CMIP5 models used in this study

Climate models	Resolution	Size of ensembles				
		ALL	ANT	GHG	AA	NAT
BCC-CSM1-1	128 × 64	3				
CanESM2	128 × 64	5		5	5	5
CCSM4	288 × 192	6	3	3	3	3
CESM1-CAM5	288 × 192	3			3	
CNRM-CM5	256 × 128	9	8	6		6
CSIRO-Mk3-6-0	192 × 96	9	5	5	5	5
FGOALS-g2	128 × 60	4				
GFDL-CM3	128 × 60	5	3	3	3	3
GISS-E2-H	144 × 90	6	5	5	5	5
GISS-E2-R	144 × 90	6	5	5	5	5
IPSL-CM5A-LR	96 × 96	6		3		3
MIROC-ESM	128 × 64	3		3		3
NorESM1-M	144 × 96	3				
Total runs (models)		68 (13)	29 (6)	38 (9)	29 (7)	38 (9)

The digits in the parentheses are the number of models

2 Data and methods

2.1 Data description

The datasets used in this study are shown as follows:

1. Observational data: the monthly mean surface air temperature Climate Research Unit (CRU) Time-Series Version 4.0 at a horizontal resolution of $0.5^\circ \times 0.5^\circ$, which is derived from the interpolation of worldwide station data and covers the period from 1901 to 2015 (Harris and Jones 2017). This data is available at <http://catalogue.ceda.ac.uk/uuid/edf8febfdaad48abb2cbaf7d7e846a86>. As has been evaluated by Hu et al. (2014), the long-term temperature changes over Central Asia derived from CRU show good agreement with that derived from the station data. This dataset has been commonly used in the study of temperature changes over arid regions (Hu et al. 2014; Guan et al. 2015; Guo et al. 2018).
2. Model simulations: as to the attribution studies on the temperature changes, model simulations from CMIP5 are employed (Taylor et al. 2012). The historical simulations driven with separated external forcings are used to estimate the corresponding contribution (Table 1). Sixty-eight runs from 13 models are driven with all-forcing (ALL), i.e., the combination of both natural and anthropogenic forcings. Both the simulations driven with only anthropogenic (ANT) forcing from 6 models and that driven with only aerosol (AA) forcing from 7 models have 29 runs. For both the simulations driven with only natural (NAT) and greenhouse gassing (GHG) forcing, 38 runs from 9 models are available. To estimate the internal variability of climate system, totally

Table 2 List of control runs of the CMIP5 models used in this study

Climate models	Years	Climate models	Years
BCC-CSM1-1	500	GISS-E2-R	850
CanESM2	996	HadGEM2-CC	241
CCSM4	501	HadGEM2-ES	338
CESM1-CAM5	319	IPSL-CM5A-LR	1000
CNRM-CM5	600	MIROC5	670
CSIRO-Mk3-6-0	500	MIROC-ESM	531
FGOALS-g2	900	MPI-ESM-LR	1000
FGOALS-s2	501	MRI-CGCM3	500
GFDL-CM3	500	NorESM1-M	501
Total years (models)			10,948 (18)

10948 years pre-industrial control runs from 18 climate models are used (Table 2). The CMIP5 projections under Representative Concentration Pathways (RCP) 4.5 and 8.5 scenarios are also used in this study to address the projected changes in the temperature over Central Asia. Only the first member of RCPs projections from 32 climate models are employed (Table 3).

2.2 Optimal fingerprinting method

To conduct the detection and attribution analysis, an optimal fingerprint method based on generalized linear regression (Allen and Tett 1999; Allen and Stott 2003; Bindoff et al. 2013; Ribes et al. 2013; Ribes and Terray 2013) is employed in this study. The optimal fingerprint method assumes that the important physical processes of climate system can be well simulated by the model. In addition, the simulated signals in response to different external forcings as well as the

Table 3 List of RCP runs of the CMIP5 models used in this study

Climate models	Climate models	RCP4.5	RCP8.5
ACCESS1-0	GFDL-ESM2G	rlilp1	rlilp1
ACCESS1-3	GFDL-ESM2 M	rlilp1	rlilp1
BNU-ESM	GISS-E2-H	rlilp1	rlilp1
CanESM2	GISS-E2-R	rlilp1	rlilp1
CCSM4	HadGEM2-AO	rlilp1	rlilp1
CESM1-BGC	HadGEM2-CC	rlilp1	rlilp1
CESM1-CAM5-1-FV2	HadGEM2-ES	rlilp1	rlilp1
CESM1-CAM5	inmcm4	rlilp1	rlilp1
CMCC-CM	IPSL-CM5A-LR	rlilp1	rlilp1
CMCC-CMS	MIROC-ESM-CHEM	rlilp1	rlilp1
CNRM-CM5	MIROC-ESM	rlilp1	rlilp1
CSIRO-Mk3-6-0	MPI-ESM-LR	rlilp1	rlilp1
FGOALS-g2	MPI-ESM-MR	rlilp1	rlilp1
FGOALS-s2	MRI-CGCM3	rlilp1	rlilp1
FIO-ESM	NorESM1-ME	rlilp1	rlilp1
GFDL-CM3	NorESM1-M	rlilp1	rlilp1
Total runs (models)		32 (32)	32 (32)

internal variability can be linearly additive. Thus, the sum of changing signals from different external forcings and internal variability is expected to be the observed changes. The total least squares regression (TLS) is employed in this study. The statistical model can be expressed as the following equation:

$$Y = \beta (X - v) + \mu.$$

Here, vector Y indicates the observed 5-year non-overlapping mean temperature record, and matrix X indicates the model simulated temperature changes in response to external forcing. β is the scaling factor which can adjust the simulation to best match observations. The significance level for the detection and attribution analysis is 10%. The corresponding influence of external forcing can be detected if the 90% confidence interval of scaling factor β is larger than zero. If scaling factor β equals 1, we conclude that the observed temperature changes are well captured by the model simulations. If scaling factor β is larger (smaller) than 1, the observed changes are underestimated (overestimated) by the model simulations. v denotes the sample errors result from a finite model ensemble. μ represents the noise or internal variability of climate system in observations which cannot be explained by the external forcing. Matrix X would be one vector for the single-signal attribution (e.g. GHG, ALL) and two vectors for the two-signal attribution (e.g. NAT and ANT). Correspondingly, the number of element for scaling factor β would be 1 or 2.

To confirm the reliability of attribution results, we test the consistency between the regression residual and model simulated noise estimates using the residual consistency test

at the 10% significance level (Allen and Tett 1999; Allen and Stott 2003), as in previous studies (Li et al. 2017a; Ma et al. 2017b; Wang et al. 2018). Note all the results shown in this study have passed the consistency test.

2.3 Observation and model data processing

Both the observation and model simulations driven by external forcing are interpolated onto the same horizontal resolution of $2.5^\circ \times 2.5^\circ$ latitude/longitude. Then, the model simulations are masked with the observations to keep consistent with the available observed data. The area-weighted method is used to calculate the regional average. Detection and attribution studies based on the optimal fingerprinting method need to accurately estimate the noise covariance matrix. Due to the limit available model simulations, or the estimated noise covariance matrix is not full rank, detection and attribution analysis must be conducted at a reduced dimension. Therefore, the multiyear non-overlapping means are employed to reasonably reduce the temporal dimension (Wen et al. 2013; Xu et al. 2015). The detection results are not sensitive to the use of time average from different years, and the 5 year is commonly used as an averaging period in previous studies (Lu et al. 2016; Li et al. 2017a; Wang et al. 2018). Thus, in this study we used the 5-year non-overlapping means for the regional averaged air temperature.

To extract the natural internal variability, the preindustrial control simulations from CMIP5 models are used. For the optimal fingerprinting method, two independent estimation of natural internal variability, one for optimization and the other for testing, are required. Thus, the 10948 year control simulations into two equal halves, of which each has 121×45 year chunks of datasets. All the chunks of preindustrial control simulations are then processed using the same methods for the model simulations driven with external forcings.

We test the significance of temperature trends in this study based on the Student's t test. The model consistency is calculated as the ratio of model numbers with changing signal same as the multi-model ensemble mean to the total model numbers over each grid.

2.4 Projection adjustment

Model simulations may overestimate (underestimate) the historical climate change of observations, resulting in the potential overestimated (underestimated) projected results. Thus, as in previous studies (Allen et al. 2000; Sun et al. 2014; Wang et al. 2018), we multiply the multi-model ensemble mean of CMIP5 projections by the best estimations of scaling factors for ALL in the single-signal optimal

Fig. 2 Area-weighted regional averaged mean surface air temperature anomalies (relative to the period 1961–1980) for Central Asia during 1961–2005. **a** ANN; **b** MAM; **c** JJA; **d** SON; **e** DJF. Black line indicates the results from CRU. Red, yellow, purple and blue lines

indicate the results from the ALL, NAT, GHG and AA forcing runs, respectively. The red and yellow shadings indicate the ± 1 standard deviations of the model simulations driven with all and natural only external forcings, respectively. Unit: $^{\circ}\text{C}$

fingerprinting analyses to address the potential overestimation (underestimation).

3 Results

3.1 Observed and model simulated regional averaged surface air temperature anomalies

We show the area-weighted regional averaged results for both annual and seasonal mean surface air temperature anomalies over Central Asia from 1961 to 2005 in Fig. 2. The observed annual mean surface air temperature over Central Asia has increased significantly (at the 5% level) (black line in Fig. 2a) during 1961–2005, with an upward rate at $0.30\text{ }^{\circ}\text{C decade}^{-1}$. This warming rate is much higher

than that for the global land (about $0.19\text{ }^{\circ}\text{C decade}^{-1}$, IPCC 2013) during past half century, demonstrating a high risk of the ecosystem over dry-lands in response to global warming.

The results from multi-model ensemble mean of ALL simulations (red line in Fig. 2a) can well capture the observed annual warming trend over Central Asia, with a rate of $0.29\text{ }^{\circ}\text{C decade}^{-1}$, which is close to the observed value. Because the results from multi-model ensemble mean mainly reflect the external forcing signal, the fluctuation of temperature evolutions from ALL simulations is smaller than that from observation. GHG (purple line in Fig. 2a) is the dominant driver for the warming trend in ALL simulations, which significantly increases the annual mean surface air temperature over Central Asia at a rate of $0.31\text{ }^{\circ}\text{C decade}^{-1}$. On the contrary, AA significantly decreases the annual mean surface air temperature over Central Asia

Fig. 3 The long-term trend ($^{\circ}\text{C } 45 \text{ year}^{-1}$) of regional area-weighted surface air temperature over Central Asia for **a** ANN, **b** MAM, **c** JJA, **d** SON, and **e** DJF. Black, red, magenta, purple, blue, and yellow bars

indicate the results from CRU, ALL, ANT, GHG, AA, and NAT, respectively. Stars indicate the trends are statistically significant at the 5% level

with a rate of $-0.08 \text{ }^{\circ}\text{C decade}^{-1}$ (blue lines in Fig. 2a). In response to natural only forcing (NAT), the annual mean temperature increases slightly at a rate of $0.01 \text{ }^{\circ}\text{C decade}^{-1}$ (yellow line in Fig. 2a), differing from the significant warming trend in observation.

The warming rate in spring ($0.18 \text{ }^{\circ}\text{C decade}^{-1}$) is not statistically significant at the 5% level (black lines in Fig. 2b). The observed significant warming trends are concentrated in summer, autumn, and winter, with a rate of $0.20 \text{ }^{\circ}\text{C decade}^{-1}$, $0.27 \text{ }^{\circ}\text{C decade}^{-1}$, and $0.55 \text{ }^{\circ}\text{C decade}^{-1}$ (black lines in Fig. 2c–e), respectively. Obviously, the warming rate in cold season is much larger than that in warm season. The observed seasonal warming trend over Central Asia can be captured by the ALL experiments (red lines in Fig. 2b–e), which shows a warming rate of $0.25 \text{ }^{\circ}\text{C decade}^{-1}$ in spring, $0.30 \text{ }^{\circ}\text{C decade}^{-1}$ in summer, $0.28 \text{ }^{\circ}\text{C decade}^{-1}$ in autumn, and $0.31 \text{ }^{\circ}\text{C decade}^{-1}$ in winter, respectively. Note all these simulated trends are statistically significant at the

5% level. CMIP5 models overestimate the spring, summer and autumn warming trend but underestimate the winter warming trend. In response to GHG forcing, the surface air temperature over Central Asia increases significantly at a rate of $0.30 \text{ }^{\circ}\text{C decade}^{-1}$ in spring, $0.31 \text{ }^{\circ}\text{C decade}^{-1}$ in summer, $0.32 \text{ }^{\circ}\text{C decade}^{-1}$ in autumn, and $0.31 \text{ }^{\circ}\text{C decade}^{-1}$ in winter, respectively (purple lines in Fig. 2b–e). Conversely, AA has resulted in the significant cooling effect in all the four seasons during 1961–2005, with a rate of $-0.07 \text{ }^{\circ}\text{C decade}^{-1}$, $-0.07 \text{ }^{\circ}\text{C decade}^{-1}$, $-0.08 \text{ }^{\circ}\text{C decade}^{-1}$ and $-0.14 \text{ }^{\circ}\text{C decade}^{-1}$ for spring, summer, autumn, and winter, respectively (blue lines in Fig. 2b–e). The trends for the seasonal mean surface air temperature from NAT simulations are positive but insignificant, at a rate of $0.01 \text{ }^{\circ}\text{C decade}^{-1}$ in the four seasons (yellow lines in Fig. 2b–e). Similar to the results for annual mean temperature, the changes in seasonal mean temperature from NAT are obviously different from the observations.

We show the observed and model-simulated warming amplitudes over Central Asia from 1961 to 2005 in Fig. 3 to examine the seasonal warming characteristics. The annual mean temperature over Central Asia has increased by 1.33 °C from 1961 to 2005 and is mainly from winter (2.48 °C), while the temperature has increased by 0.80 °C in spring, 0.90 °C in summer and 1.22 °C in autumn, respectively (black bars in Fig. 3a–e). Because of the combination of increasing GHG concentrations and weakened Siberia High, the winter over Central Asia warms faster than the other seasons (Li et al. 2012). The observed characteristic that Central Asia warms up faster in winter relative to the other seasons can be captured by the ALL experiments (red bars in Fig. 3b–d). However, the seasonal warming difference in ALL simulations is much smaller than that from observation because of the underestimated winter warming trend which is mainly result from the contribution of GHG (purple bars in Fig. 3b, d). This underestimated winter warming is owing to that observed warming is the sum of dynamically and radiatively forced changes but CMIP5 models can only reproduce the latter one (Guan et al. 2015). We note the cooling effect of AA has an obvious seasonal characteristic, with a magnitude in winter (-0.61 °C) nearly twice more than that in summer (-0.32 °C) (blue lines in Fig. 3c, e). The much stronger cooling effect in winter results from a faster decreasing trend of the downward shortwave radiation in response to AA forcing (figures not shown).

3.2 Spatial pattern for the observed and simulated temperature trend

The spatial patterns for the trend of annual mean temperature from observation, ALL, ANT, GHG, AA and NAT simulations are shown in Fig. 4. The observed annual mean temperature increases significantly over the whole Central Asia, with two strong warming centers over eastern (larger than 1.40 °C 45 year $^{-1}$) and southwestern (about 1 °C 45 year $^{-1}$) part of Central Asia (Fig. 4a). The observed uniform warming pattern over Central Asia can be captured by the multi-model ensemble mean of ALL experiments, but with an overestimated (underestimated) magnitude over northern (southern) Central Asia. This underestimation (overestimation) can be explained by the responses to GHG forcing, which results in a larger warming rate at a higher latitude region (Fig. 4e). This is due to the larger magnitude of increased downward longwave radiation at higher latitude in response to GHG forcing (figures not shown). The annual mean temperature in response to AA forcing shows stronger cooling trend at lower latitude regions, which is similar to the spatial pattern from GHG forcing but with opposite sign. In response to NAT forcing, the annual mean temperature increases slightly over most regions of Central Asia, but

with larger warming amplitude in the eastern Central Asia (Fig. 4d).

The consistencies of changing signals from different model runs are denoted by the black dots in Fig. 4. Results show that the consistencies of temperature changes in response to ALL, ANT and GHG forcings are high, with more than 80% of the model runs have the same changing signals over the whole Central Asia. The simulated temperature changes in response to NAT forcing show a large spread among the model runs, as convinced by the evidence that none of the regions over Central Asia have the consistent temperature changing signals from more than 80% of the model runs (Fig. 4d). In response to AA forcing, the model-simulated temperature changes only show good agreement in southern Central Asia (Fig. 4f).

The observed warming rate in winter is much larger than the other seasons, dominating the annual warming in Central Asia. Thus, the spatial patterns for the observed and simulated winter temperature trend are further examined (Fig. 5). The observed winter temperature increases over the whole Central Asia, showing higher warming rate at higher latitude region, with two significant warming centers (larger than 2.80 °C 45 year $^{-1}$) over northwestern and northeastern Central Asia, respectively (Fig. 5a).

The observed warming pattern with higher warming rate at higher latitude is well captured by the multi-model ensemble mean of ALL simulations. However, the winter warming magnitudes are underestimated by the CMIP5 models over the whole Central Asia (Fig. 5b), which is responsible for the underestimated annual warming magnitudes in Fig. 4b. As in previous studies (Li et al. 2012; Wallace et al. 2012), the observed cold season warming in recent decades over Central Asia is a result of both dynamically and radiatively induced changes. However, climate models can well capture the radiatively forced changes but fail in reproducing the dynamically induced components, resulting in the underestimated winter warming trend in Central Asia (Wallace et al. 2012; Guan et al. 2015).

The warming pattern and amplitude from GHG simulations (Fig. 5e) match well with that from ALL simulations, demonstrating the dominant role of GHG forcing in regional cold season warming. AA shows a strong cooling effect in winter over the whole central Asia, and decreases the winter temperature by more than 0.40 °C during past 45 years, with a cooling center over western part lower than -0.60 °C (Fig. 5f). Note the cooling effect of AA forcing in winter is much stronger than the other seasons over the whole Central Asia (figures not shown). The influence of NAT forcing on the changes in winter temperature over Central Asia is slight (Fig. 5d), which is similar to the results from other seasons. The warming magnitude from ANT is much smaller than that from ALL despite the slight effect of NAT, which results

Fig. 4 Linear trends for annual mean temperature ($^{\circ}\text{C } 45 \text{ year}^{-1}$) during 1961–2005 from **a** CRU, **b** ALL, **c** ANT, **d** NAT, **e** GHG, and **f** AA. Model trends were calculated from the multi-model means.

White dots in **a** indicate the trends are statistically significant at the 5% level. Black dots in **b–f** indicate that exceed 80% of the model runs have the same changing signal

from the different models used in ANT and ALL (figures not shown).

In response to both ALL and GHG forcings, the changing signals of winter temperature from different model runs show good agreement over nearly the whole Central Asia. In response to both ANT and AA forcings, however, the good agreement of model simulations is only found in southern and eastern part of Central Asia (Fig. 5c). Model simulated changes in winter temperature in response to NAT forcing show large spread over the whole Central Asia. We also checked the agreement of model-simulated temperature changes in summer and autumn, which shows similar results to that in winter.

3.3 Detection and attribution results

In this section, we perform the one-signal and two-signal detection analysis on the 5-year mean annual and seasonal mean temperature series to attribute the observed historical warming over Central Asia.

We show the best estimates of scaling factors and their 90% confidence intervals for the external forcing based on the optimal analysis of the annual and seasonal mean temperature in Fig. 6. The best estimates of the scaling factors for ALL, ANT, and GHG in the single-signal analysis of annual mean temperature are 1.13 (90% confidence interval 0.56–1.72), 1.34 (0.59–2.14), and 0.89 (0.37–1.42),

Fig. 5 Same as Fig. 4, but for the results in winter

respectively (Fig. 6a). This indicates that the signals of ALL, ANT, and GHG can be robustly detected in the observed annual temperature changes over Central Asia.

The best estimate of the scaling factor for ALL is larger than 1, meaning that the observed annual mean temperature changes are underestimated by the multi-model simulations in response to ALL. All the detection results pass the residual consistency test, suggesting the good agreement between observed variability and model simulations. In the two-signal analysis, the best estimates of the scaling factors for ANT and NAT are 1.35 (0.60–2.13) and 0.92 (–0.31 to 2.24), respectively, which suggests that the effect of ANT can be separated from that of NAT. The best estimates of scaling factors for ANT from two-signal analysis

are comparable with that from single-signal analysis, indicating the robustness of human influence on the annual mean temperature changes. Thus, only the anthropogenic forcing can explain the observed annual mean temperature changes in Central Asia from 1961 to 2005.

As evidenced by the best estimates of the scaling factors in the single-signal analysis (Fig. 6c–e), the influence of ALL, ANT, and GHG forcings on the significant seasonal (summer, autumn, and winter) warming over Central Asia can be detected robustly. The best estimates of the scaling factors for ALL in the single-signal analysis are 0.73 (0.21–1.27) in summer, 0.91 (0.40–1.44) in autumn, and 1.78 (0.75–2.87) in winter. These suggest that model simulations in response to ALL forcing overestimate the changes

Fig. 6 The scaling factors for **a** ANN, **b** MAM, **c** JJA, **d** SON, and **e** DJF. Dots indicate the best estimations and the vertical bars indicate their 5–95% uncertainty confidence intervals. The results from single-

signal analysis (ALL, ANT, and GHG) and two-signal analysis (ANT and NAT) are shown in each figure from left to right

in summer and autumn mean temperature but underestimate the changes in winter mean temperature over Central Asia, which confirms that the underestimated annual warming trend results from the underestimated winter warming trend in recent decades. Based on the results of two-signal analysis, we show that the influence of ANT on the seasonal significant warming over Central Asia can be well separated from that of NAT. Therefore, human influence dominates the summer, autumn, and winter warming over Central Asia during 1961–2005. The best estimates of scaling factors for spring results are smaller than 0, indicating that the influence of external forcings on insignificant spring warming cannot be detected (Fig. 6b).

The above results based on optimal analysis suggest that the influence of ALL, ANT, and GHG on the changes in annual and summer, autumn, and winter mean temperature over Central Asia are detectable. Meanwhile, model

simulations in response to different external forcings tend to overestimate or underestimate the observed temperature trends. Therefore, following previous studies (Xu et al. 2015; Wang et al. 2017), we multiply the scaling factors by the corresponding warming trend (Fig. 4) to quantify the contributions of different external forcings to the observed annual and seasonal warming over Central Asia, as shown in Fig. 7. From 1961 to 2005, ALL has increased the observed annual, summer, autumn, and winter mean temperature by 1.45 °C (0.72–2.21 °C), 0.99 °C (0.28–1.71 °C), 1.17 °C (0.51–1.85 °C), and 2.51 °C (1.06–4.04 °C), respectively. The annual, summer, autumn, and winter warming attributable to ANT are 1.33 °C (0.59–2.10 °C), 0.98 °C (0.26–1.72 °C), 1.04 °C (0.30–1.78 °C), and 2.26 °C (0.64–4.09 °C), respectively. The contributions of NAT to the observed annual, summer, autumn, and winter mean temperature changes from 1961 to 2005 are 0.04 °C (–0.01

Fig. 7 Attributing warming (°C) and its 5–95% confidence intervals of surface air temperature change in Central Asia. Attributable warming for ALL and GHG are based on single-signal analysis, whereas

those for ANT and NAT are based on two-signal analysis. **a** ANN, **b** JJA, **c** SON, and **d** DJF

to 0.10 °C), 0.02 °C (−0.03 to 0.08 °C), 0.05 °C (−0.02 to 0.13 °C), and 0.00 °C (−0.09 to 0.08 °C), respectively, showing large uncertainty. The attributable warming from NAT is lower than that from ANT, which is dominated by the multi-decadal timescale effect because the temperature increases faster in ALL (red lines in Fig. 2) than in NAT (yellow lines in Fig. 2) after the 1980s. Obviously, the warming over Central Asia is dominated by the GHG forcing, which increases the observed annual, summer, autumn, and winter mean temperature by 1.25 °C (0.52–2.00 °C), 1.11 °C (0.32–1.92 °C), 1.11 °C (0.40–1.83 °C), and 2.5 °C (0.91–4.34 °C) from 1961 to 2005, respectively.

3.4 Projected temperature changes constrained by attribution results

The projected changes in regional averaged annual and seasonal mean temperature over Central Asia from CMIP5 simulations are shown in Fig. 8 (yellow and purple lines). The annual mean temperature over Central Asia would increase significantly, at a rate of 0.28 (0.10–0.43) and 0.65 (0.42–0.84) °C decade^{−1} during twenty-first century, under RCP4.5 and RCP8.5 scenarios, respectively (Table 4). The significant warming trend can be found in all the seasons during twenty-first century, with a rate of 0.28 (0.13–0.40) and 0.66 (0.38–0.83) °C decade^{−1} in summer, 0.26 (0.10–0.41) and 0.63 (0.43–0.80) in autumn,

and 0.32 (0.10–0.51) and 0.70 (0.40–0.90) °C decade^{−1} in winter under RCP4.5 and RCP8.5 scenarios, respectively. The higher RCPs, the larger increasing rates. To the end of twenty-first century, under RCP8.5 scenarios, the annual mean temperature over Central Asia would increase by 6.11 (3.95–7.90) °C, while the summer, autumn, and winter mean temperature would increase by 6.20 (3.57–7.47) °C, 5.92 (4.04–7.52) °C, and 6.58 (3.76–8.46) °C, respectively. Consistent with the warming trends in the historical simulation, no significant seasonal dependence of the temperature trends over Central Asia is seen in the projection, as reported in IPCC AR5 (IPCC 2013).

As revealed in the above detection results, however, the observed changes in annual and winter (summer and autumn) mean temperature are underestimated (overestimated) in the CMIP5 model simulations. These imply that the projected changes in annual and winter (summer and autumn) mean temperature over Central Asia during twenty-first century may also be underestimated (overestimated) by the CMIP5 projections.

To address the potential underestimation and overestimation, following previous studies (Allen et al. 2000; Sun et al. 2014; Wang et al. 2018), we multiply the multi-model ensemble mean of CMIP5 projections by the best estimations of scaling factors for ALL in the single-signal analyses (red lines in Fig. 6), as shown in the red and blue lines of Fig. 8. Under RCP4.5 and RCP8.5 scenarios, the corrected results

Fig. 8 Temperature anomalies (relative to the period 1986–2005) during 1961–2099. Future projection of temperature change is based on the multi-model means under RCP4.5 (blue and purple lines) and RCP8.5 (red and yellow lines). Black lines indicate the historical results. The yellow and purple lines indicate the raw projection results (with prefix “r”). The red and blue lines indicate the corrected

projection results (with prefix “c”) based on the best estimated scaling factors from ALL runs. Purple and yellow shadings indicate the 5–95% uncertainty range from uncorrected multi-model runs. Red and blue shadings indicate the 5–95% uncertainties of corrected projections estimated based on the uncertainties of scaling factors from ALL runs. Unit: °C

Table 4 The projected temperature trends and the 5–95% uncertainties over Central Asia during 2006–2099 from raw (with prefix “r”) and corrected (with prefix “c”) CMIP5 projections

	rRCP4.5	rRCP8.5	cRCP4.5	cRCP8.5
ANN	0.28 (0.10–0.43)	0.65 (0.42–0.84)	0.32 (0.16–0.49)	0.74 (0.36–1.12)
JJA	0.28 (0.13–0.40)	0.66 (0.38–0.83)	0.20 (0.06–0.35)	0.48 (0.14–0.84)
SON	0.26 (0.10–0.41)	0.63 (0.43–0.80)	0.24 (0.10–0.38)	0.58 (0.25–0.91)
DJF	0.32 (0.10–0.51)	0.70 (0.40–0.90)	0.58 (0.24–0.93)	1.25 (0.53–2.02)

Unit: °C decade⁻¹. All the trends are statistically significant at the 5% level

indicate that the annual mean temperature over Central Asia would significantly increase at a rate of 0.32 (0.16–0.49) and 0.74 (0.36–1.12) °C decade⁻¹, while the summer, autumn, and winter mean temperature would increase at a rate of 0.20 (0.06–0.35) and 0.48 (0.14–0.84) °C decade⁻¹, 0.24 (0.10–0.38) and 0.58 (0.25–0.91) °C decade⁻¹, and 0.58 (0.24–0.93) and 1.25 (0.53–2.02) °C decade⁻¹, respectively. Therefore, unlike the conclusion “CMIP5 projected temperature increase in Central Asia of comparable magnitude in both JJA and in DJF” reported in IPCC AR5 (Section 14.8.8, page 1269) (IPCC 2013), the corrected results show much larger warming rate in winter than that in summer, showing a large annual variation. To the end of twenty-first century, the corrected annual mean temperature over Central Asia would increase by 7.00 °C under RCP8.5 scenarios, 0.85 °C higher

than the uncorrected results. The projected higher annual mean temperature over Central Asia mainly results from the warmer winter after correction. As shown in Fig. 8d, the corrected winter mean temperature over Central Asia would increase by 11.75 °C under RCP8.5, 5.17 °C higher than the uncorrected results.

We also show the spatial patterns of projected temperature changes under RCP8.5 during 2080–2099 in Fig. 9. The annual and seasonal mean temperature projected by CMIP5 models would increase significantly over the whole Central Asia (Fig. 9a–d). The largest annual mean warming magnitude are seen in the north of Central Asia (larger than 7 °C), which results from the winter warming (larger than 8 °C). Adjusted by the scaling factors from attribution results, the annual and winter (summer and autumn) mean temperature

Fig. 9 Spatial patterns of the projected temperature changes during 2081–2099 (with respect to the period 1986–2005) under RCP8.5 scenario. The rows from top to bottom indicate the results of annual, summer, autumn, and winter mean. The columns from left to right

indicate the raw and corrected results, and the difference between those two. Black dots indicate that exceed 80% of the model runs have the same changing signal. Unit: °C

over Central Asia would increase at a larger (smaller) magnitude (Fig. 9e–h). Compared to the unadjusted results, the adjusted annual mean temperature in north Central Asia would increase at a magnitude of 1.0 °C higher, which is mainly from the higher winter warming magnitude (more than 5.5 °C), while the summer and autumn mean temperature would be less warming (Fig. 9i–k). As a result, the annual variation of warming trend would be larger over the whole Central Asia.

4 Summary

The observed surface air temperature over arid and semi-arid Central Asia has shown a significant increasing trend during 1961–2005, resulting in great influence on the local ecosystem. However, whether the influence of anthropogenic forcings on the temperature changes can be detected remains unclear. Thus, based on the CMIP5 model simulations, we employ the optimal fingerprinting method to detect and

attribute the annual and seasonal mean temperature changes in Central Asia during 1961–2005 and then adjust the temperature projections based on the attributing results. The main results are summarized as follows:

The observed annual mean temperature over Central Asia has significantly increased by 1.33 °C from 1961 to 2005, which is concentrated in summer (0.90 °C), autumn (1.22 °C), and winter (2.48 °C). The CMIP5 model simulations driven by all forcings can well reproduce the observed significant warming from 1961 to 2005, with 1.31 °C for annual mean, 1.35 °C in summer, 1.26 °C in autumn, and 1.40 °C in winter. The seasonal dependence of observed warming trends over Central Asia is not well captured by the CMIP5 models because of the underestimated (overestimated) annual and winter (summer and autumn) warming trend.

Attribution results suggest that the influence of ALL, ANT, and GHG forcings on both the observed annual and seasonal mean temperature changes over Central Asia can be detected robustly. All the results pass the consistency test at the 10% significance level. Human influence is the main contributor to the observed warming over Central Asia in recent decades. From 1961 to 2005, GHG has increased the annual mean temperature over Central Asia by 1.25 °C (0.52–2.00 °C), and has increased the summer, autumn, and winter mean temperature by 1.11 °C (0.32–1.92 °C), 1.11 °C (0.40–1.83 °C), and 2.50 °C (0.91–4.34 °C), respectively. The influence of NAT forcing on the observed temperature changes has a large uncertainty and cannot be robustly detected.

CMIP5 simulations underestimate (overestimate) the observed annual and winter (summer and autumn) warming trend during 1961–2005, which may results in the projection bias. Therefore, the CMIP5 projections are corrected based on the attribution results to address the potential underestimations and overestimations. The corrections show that the annual, summer, autumn, and winter mean temperature over Central Asia would significantly increase at a rate of 0.32 (0.16–0.49) °C decade⁻¹, 0.20 (0.06–0.35) °C decade⁻¹, 0.24 (0.10–0.38) °C decade⁻¹, and 0.58 (0.24–0.93) °C decade⁻¹ under RCP4.5, while 0.74 (0.36–1.12) °C decade⁻¹, 0.48 (0.14–0.84) °C decade⁻¹, 0.58 (0.25–0.91) °C decade⁻¹, and 1.25 (0.53–2.02) °C decade⁻¹ under RCP8.5, respectively. Thus, the large annual variation of warming magnitude would be seen in the future, which is different from the conclusion “CMIP5 projected temperature increase in Central Asia of comparable magnitude in both JJA and in DJF” reported in IPCC AR5 (Section 14.8.8, page 1269). To the end of twenty-first century, the annual (winter) mean temperature over Central Asia would increase by 7.00 °C (11.75 °C) under RCP8.5 scenarios, 0.85 °C (5.17 °C) higher than the uncorrected results, with the largest warming magnitude would be seen in north Central Asia.

We acknowledge the discrepancies of CMIP5 models in simulating historical temperature changes over Central Asia. While the observed seasonal warming associated with changes in radiative forcings are well simulated in the context of regional average, discrepancies are seen in both the spatial patterns and the seasonal dependence of warming trend. These weaknesses are resulted from the limitations of climate models in capturing the dynamically forced temperature changes associated with internal climate variability, including Atlantic Multi-decadal Oscillation (AMO), Pacific Decadal Oscillation (PDO), North Atlantic Oscillation (NAO), and the weakening winter Siberia High (Li et al. 2012, 2013b; Guan et al. 2015; Dong and Dai 2015; Guo et al. 2018). How the internal variability modes influence the decadal surface air temperature changes over Central Asia is beyond the scope of this research but deserves further study.

Scaling based on the historical attributed scaling factors is a useful way to narrow or reduce the uncertainties of projections in the climate community. Since the uncertainty of future temperature changes associated with internal variability is negligible in mid and long-term climate projections (Hawkins and Sutton 2009, 2011), the scaling technique is hoped to reduce the uncertainty arisen from model structure mostly due to different climate sensitivities (Zhou and Chen 2015). Nonetheless, as evidenced by our analysis, the spread is still large after the scaling adjustment. Another limitation of the method is the difficulty to consider the spatial patterns of the projected warming trend. We hope the progress in the development of climate models will help to reduce the model uncertainty. The new CMIP6 project will provide opportunity in the coming years.

Acknowledgements This work is mainly supported by the Strategic Priority Research Program of the Chinese Academy of Sciences (Grant no. XDA20060102). L. Zhang is supported by the Ministry of Science and Technology of China under Grant 2018YFA0606501. D. Peng is also supported by the National Natural Science Foundation of China (Grant no. 41575043). We also acknowledge the support from *Jiangsu Collaborative Innovation Center for Climate change*.

Open Access This article is distributed under the terms of the Creative Commons Attribution 4.0 International License (<http://creativecommons.org/licenses/by/4.0/>), which permits unrestricted use, distribution, and reproduction in any medium, provided you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license, and indicate if changes were made.

References

- Allen MR, Stott PA (2003) Estimating signal amplitudes in optimal fingerprinting. Part I: theory. *Clim Dyn* 21(5–6):477–491. <https://doi.org/10.1007/s00382-003-0313-9>
- Allen MR, Tett SFB (1999) Checking for model consistency in optimal fingerprinting. *Clim Dyn* 15(6):419–434

- Allen MR, Stott PA, Mitchell JFB et al (2000) Quantifying the uncertainty in forecasts of anthropogenic climate change. *Nature* 407:617–620. <https://doi.org/10.1038/35036559>
- Bai L, Xu J, Chen Z et al (2015) The regional features of temperature variation trends over Xinjiang in China by the ensemble empirical mode decomposition method. *Int J Climatol* 35(11):3229–3237. <https://doi.org/10.1002/joc.4202>
- Bindoff N, Stott P, AchutaRao KM et al (2013) Detection and attribution of climate change: from global to regional. In: Stocker TF, Qin DH, Plattner GK, Tignor M, Allen SK, Boschung J, Nauels A, Xia Y, Bex V, Midgley PM (eds) *Climate change 2013: the physical science basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge
- Chen FH, Huang W, Jin LY et al (2011) Spatiotemporal precipitation variations in the arid Central Asia in the context of global warming. *Sci China Earth Sci* 54(12):1812–1821. <https://doi.org/10.1007/s11430-011-4333-8>
- Chen Y, Li W, Deng H et al (2016) Changes in Central Asia's water tower: past, present and future. *Sci Rep* 6:35458. <https://doi.org/10.1038/srep39364>
- Deng H, Chen Y, Shi X et al (2014) Dynamics of temperature and precipitation extremes and their spatial variation in the arid region of northwest China. *Atmos Res* 138:346–355. <https://doi.org/10.1016/j.atmosres.2013.12.001>
- Dong B, Dai A (2015) The influence of the interdecadal Pacific oscillation on temperature and precipitation over the globe. *Clim Dyn* 45(9–10):2667–2681
- Dong W, Lin Y, Wright JS et al (2018) Regional disparities in warm season rainfall changes over arid eastern–central Asia. *Sci Rep* 8(1):13051. <https://doi.org/10.1038/s41598-018-31246-3>
- Guan X, Huang J, Guo R et al (2015) Role of radiatively forced temperature changes in enhanced semi-arid warming over East Asia. *Atmos Chem Phys* 15(23):13777–13786. <https://doi.org/10.5194/acp-15-13777-2015>
- Guo R, Guan X, He Y et al (2018) Different roles of dynamic and thermodynamic effects in enhanced semi-arid warming. *Int J Climatol* 38(1):13–22. <https://doi.org/10.1002/joc.5155>
- Harris IC, Jones PD (2017) CRU TS4.00: Climatic Research Unit (CRU) Time-Series (TS) version 4.00 of high-resolution gridded data of month-by-month variation in climate (Jan. 1901–Dec. 2015). Centre for Environmental Data Analysis, 25 August 2017. <https://doi.org/10.5285/edf8febfdad48abb2cbaf7d7e846a86>
- Hawkins E, Sutton R (2009) The potential to narrow uncertainty in regional climate predictions. *Bull Am Meteorol Soc* 90(8):1095–1108
- Hawkins E, Sutton R (2011) The potential to narrow uncertainty in projections of regional precipitation change. *Clim Dyn* 37(1–2):407–418
- Hegerl G, Zwiers F (2011) Use of models in detection and attribution of climate change. *Wiley Interdiscip Rev Clim Change* 2(4):570–591. <https://doi.org/10.1002/wcc.121>
- Hu Z, Zhang C, Hu Q et al (2014) Temperature changes in Central Asia from 1979 to 2011 based on multiple datasets. *J Clim* 27(3):1143–1167. <https://doi.org/10.1175/JCLI-D-13-00064.1>
- Hu Z, Zhou Q, Chen X et al (2017) Variations and changes of annual precipitation in Central Asia over the last century. *Int J Climatol* 37(S1):157–170. <https://doi.org/10.1002/joc.4988>
- Huang J, Ji M, Xie Y et al (2016a) Global semi-arid climate change over last 60 years. *Clim Dyn* 46(3–4):1131–1150. <https://doi.org/10.1007/s00382-015-2636-8>
- Huang J, Yu H, Guan X et al (2016b) Accelerated dryland expansion under climate change. *Nat Clim Change* 6(2):166–171. <https://doi.org/10.1038/NCLIMATE2837>
- Huang J, Yu H, Dai A et al (2017) Drylands face potential threat under 2 °C global warming target. *Nat Clim Change* 7(6):417–422. <https://doi.org/10.1038/NCLIMATE3275>
- Intergovernmental Panel on Climate Change (IPCC) (2013) In: Stocker TF et al (eds) *Climate Change 2013: the physical science basis: working group I contribution to the fifth assessment report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge
- Li B, Chen Y, Shi X (2012) Why does the temperature rise faster in the arid region of northwest China? *J Geophys Res Atmos* 117:D16115. <https://doi.org/10.1029/2012jd017953>
- Li B, Chen Y, Shi X et al (2013a) Temperature and precipitation changes in different environments in the arid region of northwest China. *Theor Appl Climatol* 112(3–4):589–596. <https://doi.org/10.1007/s00704-012-0753-4>
- Li J, Sun C, Jin F (2013b) NAO implicated as a predictor of Northern Hemisphere mean temperature multidecadal variability. *Geophys Res Lett* 40(20):5497–5502
- Li Y, Huang J, Ji M et al (2015) Dryland expansion in northern China from 1948 to 2008. *Adv Atmos Sci* 32(6):870–876. <https://doi.org/10.1007/s00376-014-4106-3>
- Li B, Chen Y, Chen Z et al (2016) Why does precipitation in northwest China show a significant increasing trend from 1960 to 2010? *Atmos Res* 167:275–284. <https://doi.org/10.1016/j.atmosres.2015.08.017>
- Li C, Zhao T, Ying K (2017a) Quantifying the contributions of anthropogenic and natural forcings to climate changes over arid-semiarid areas during 1946–2005. *Clim Change* 144(3):505–517. <https://doi.org/10.1007/s10584-017-2028-7>
- Li Z, Chen Y, Fang G et al (2017b) Multivariate assessment and attribution of droughts in Central Asia. *Sci Rep* 7:1316. <https://doi.org/10.1038/s41598-017-01473-1>
- Lu C, Sun Y, Wan H et al (2016) Anthropogenic influence on the frequency of extreme temperatures in China. *Geophys Res Lett* 43(12):6511–6518. <https://doi.org/10.1002/2016GL069296>
- Ma S, Zhou T, Stone DA et al (2017a) Attribution of the July–August 2013 heat event in Central and Eastern China to anthropogenic greenhouse gas emissions. *Environ Res Lett* 12(5):054020. <https://doi.org/10.1088/1748-9326/aa69d2>
- Ma S, Zhou T, Stone DA et al (2017b) Detectable anthropogenic shift toward heavy precipitation over eastern China. *J Clim* 30(4). <https://doi.org/10.1175/jcli-d-16-0311.1>
- Peng D, Zhou T (2017) Why was the arid and semiarid Northwest China getting wetter in the recent decades? *J Geophys Res Atmos* 122(17):9060–9075. <https://doi.org/10.1002/2016JD026424>
- Peng D, Zhou T, Zhang L et al (2018) Human contribution to the increasing summer precipitation in Central Asia from 1961 to 2013. *J Clim* 31(19):8005–8021. <https://doi.org/10.1175/JCLI-D-17-0843.1>
- Ribes A, Terray L (2013) Application of regularised optimal fingerprint to attribution. Part II: application to global near-surface temperature. *Clim Dyn* 41(11–12):2837–2853. <https://doi.org/10.1007/s00382-013-1736-6>
- Ribes A, Planton S, Terray L (2013) Application of regularised optimal fingerprinting to attribution. Part I: method, properties and idealised analysis. *Clim Dyn* 41(11–12):2817–2836. <https://doi.org/10.1007/s00382-013-1735-7>
- Rodell M, Famiglietti JS, Wiese DN et al (2018) Emerging trends in global freshwater availability. *Nature* 557(7707):651. <https://doi.org/10.1038/s41586-018-0123-1>
- Shi YF, Shen YP, Kang E et al (2007) Recent and future climate change in northwest China. *Clim Change* 80(3–4):379–393. <https://doi.org/10.1007/s10584-006-9121-7>
- Song L, Dong S, Sun Y et al (2015) Role of anthropogenic forcing in 2014 hot spring in Northern China. *Bull Am Meteorol Soc*

- 96(12):S111–S114. <https://doi.org/10.1175/BAMS-D-15-00111.1>
- Stott PA, Gillett NP, Hegerl GC et al (2010) Detection and attribution of climate change: a regional perspective. *Wiley Interdiscip Rev Clim Change* 1(2):192–211. <https://doi.org/10.1002/wcc.34>
- Sun Y, Zhang X, Zwiers F et al (2014) Rapid increase in the risk of extreme summer heat in Eastern China. *Nat Clim Change* 4(12):1082–1085. <https://doi.org/10.1038/NCLIMATE2410>
- Sun Y, Song L, Yin H et al (2016a) Human influence on the 2015 extreme high temperature events in western China. *Bull Am Meteorol Soc* 97(12):S102–S106
- Sun Y, Zhang X, Ren G et al (2016b) Contribution of urbanization to warming in China. *Nat Clim Change* 6(7):706–709. <https://doi.org/10.1038/NCLIMATE2956>
- Taylor KE, Stouffer RJ, Meehl GA (2012) An overview of CMIP5 and the experiment design. *Bull Am Meteorol Soc* 93(4):485–498. <https://doi.org/10.1175/BAMS-D-11-00094.1>
- Wallace JM, Fu Q, Smoliak BV et al (2012) Simulated versus observed patterns of warming over the extratropical Northern Hemisphere continents during the cold season. *Proc Natl Acad Sci* 109(36):14337–14342. <https://doi.org/10.1073/pnas.1204875109>
- Wang Y, Zhou B, Qin D et al (2017) Changes in mean and extreme temperature and precipitation over the arid region of northwestern China: observation and projection. *Adv Atmos Sci* 34(3):289–305. <https://doi.org/10.1007/s00376-016-6160-5>
- Wang Y, Sun Y, Hu T et al (2018) Attribution of temperature changes in Western China. *Int J Climatol* 38(2):742–750. <https://doi.org/10.1002/joc.5206>
- Wen HQ, Zhang X, Xu Y et al (2013) Detecting human influence on extreme temperatures in China. *Geophys Res Lett* 40(6):1171–1176. <https://doi.org/10.1002/grl.50285>
- Xu Y, Gao X, Shi Y et al (2015) Detection and attribution analysis of annual mean temperature changes in China. *Clim Res* 63(1):61–71. <https://doi.org/10.3354/cr01283>
- Yin H, Sun Y, Wan H et al (2017) Detection of anthropogenic influence on the intensity of extreme temperatures in China. *Int J Climatol* 37(3):1229–1237. <https://doi.org/10.1002/joc.4771>
- Zhao C, Yao S, Liu J et al (2014) The spatial distribution of precipitation in northwest China. *J Electr Comput Eng* 1:1–5. <https://doi.org/10.1155/2014/514291>
- Zhou T, Chen X (2015) Uncertainty in the 2°C warming threshold related to climate sensitivity and climate feedback. *J Meteorol Res* 29(6):884–895. <https://doi.org/10.1007/s13351-015-5036-47>
- Zhou T, Ma S, Zou L (2014) Understanding a hot summer in central eastern China: summer 2013 in context of multimodel trend analysis. *Bull Am Meteorol Soc* 95(9):S54–S57
- Zhou T, Sun N, Zhang W et al (2018) When and how will the Millennium Silk Road witness 1.5 °C and 2 °C warmer worlds? *Atmos Ocean Sci Lett* 11(2):180–188. <https://doi.org/10.1080/16742834.2018.1440134>

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.