Geophysical Research Letters

RESEARCH LETTER
10.1029/2018GL079133

Key Points:
- Significant influence of anthropogenic on extreme precipitation events in China has not yet emerged within the observational record (1961-2012)
- An anthropogenic signal of changes in extreme precipitation events would be detectable by around 2035 under RCP8.5 scenario
- Large changes would manifest by the time of signal detection; extreme precipitation events that occur once every 20, 50, and 100 years in the current (1986-2005) climate will occur once every 15, 34, and 63 years by that time

Supporting Information:
- Supporting Information S1

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Citation:
Li, W., Jiang, Z., Zhang, X., & Li, L. (2018). On the emergence of anthropogenic signal in extreme precipitation change over China. *Geophysical Research Letters*, *45*, 9179–9185. https://doi.org/10.1029/2018GL079133

Received 26 JUN 2018
Accepted 26 JUL 2018
Accepted article online 2 AUG 2018
Published online 12 SEP 2018

On the Emergence of Anthropogenic Signal in Extreme Precipitation Change Over China

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Abstract The detection of anthropogenic influences on climate extremes at regional scale is important for the development of national climate change policy. Global climate simulations from phase 5 of the Coupled Model Intercomparison Project under the Representative Concentration Pathway 8.5 scenario are used to examine the time at which an anthropogenic influence becomes detectable in extreme precipitation over China and the change in probability of extreme precipitation with certain magnitudes when the changes are detectable. Anthropogenic influence is not significantly detected over China in the observational record or simulations from 1961 to 2012 based on the test of field significance. Simulations indicate that such change would become detectable in the future by around 2035. Large changes would already manifest by the time of signal detection; for example, extreme precipitation events that occur on average once every 20, 50, and 100 years in current (1986–2005) climate would reduce to about 15, 34, and 63 years on average by the time of detection around 2035.

Plain Language Summary Understanding causes of changes in extreme precipitation can enhance our confidence in future projections of extreme precipitation. The attribution of cause in changes of extreme precipitation is not straightforward at regional scale, due to the presence of strong natural variability in Earth's climate and the lack of long-term and reliable observational records. This work seeks the anthropogenic signal in extreme precipitation events within the current observational record. It also uses climate models to explore the time at which such a signal would emerge in the future and to assess the associated risks of extreme precipitation events over China. The findings help us to understand the future evolution of Earth's climate and provide useful information for the design and implementation of climate adaptation measures.

1. Introduction

The risk of flooding caused by extreme precipitation events is a major threat to human societies across the world. There is a need to investigate potential future changes in extreme precipitation events resulting from global warming due to anthropogenic emissions of greenhouse gases. Determination of the cause of changes in extreme precipitation events or their association with other changes in the climate system can provide us some confidence in future projections of climate change. Many reports have shown upward trends in extreme precipitation events at the global or continental scale based on observations (Alexander et al., 2006; Westra et al., 2012), and it has been suggested that such trends may be attributable to anthropogenic global warming (Min et al., 2011; Zhang et al., 2013). Projections under future scenarios have indicated that the incidence of extreme precipitation events will continue to increase with further global warming (Kharin et al., 2013; Sillmann et al., 2013).

The high level of natural variability in relation to expected warming-induced changes along with a lack of long-term, reliable observational data limit the detection of anthropogenic influence on extreme precipitation at regional scale (Stott et al., 2010). However, it is crucial for policymakers developing regional prevention schemes for natural disasters to address these issues. Sufficiently reliable future projections of changes in extreme precipitation are very helpful in developing adequate mitigation schemes for extreme changes in climate. Many studies showed clearly that GCMs have certain capability to reproduce the observed extreme precipitation at region scale, including spatial patterns and regional averages (Jiang et al., 2015; W. Li, Jiang, et al., 2017), although the observed trend of extreme precipitation is hardly well simulated (Ou et al., 2013). A natural question regarding changes of extreme precipitation is the emergence of a regional-scale anthropogenic signal. Addressing this question may provide useful information for policymakers. Much work has been published in recent years on estimating the timing of the emergence of an anthropogenic signal at regional scale, and those studies have consistently reported that an anthropogenic signal of changes in extreme precipitation events would emerge in the few decades (Fowler et al., 2010; King et al., 2015; Maraun, 2013; Martel et al., 2018).

Some studies have found increases in the intensity and probability of extreme precipitation over China in the future with global warming (Feng et al., 2011; W. Li et al., 2016; W. Li, Jiang, et al., 2017; Zhou et al., 2014). However, few studies have focused on the timing of the emergence of climate change signal from natural variability. Here we applied a statistical approach to show that significant anthropogenic influence in extreme precipitation over China is not yet significantly detectable from the available observational data and that such change would emerge in about 20 years in GCMs simulations. We will also show that the changes in the probability of extreme precipitation are substantial when the signal emerges.

2. Data and Analysis Methodology

2.1. Observational Data

We used daily precipitation data collected by the China Meteorological Administration from 726 meteorological stations in the period 1961 to 2012 (available online at http://data.cma.cn/data/cdcdetail/dataCode/A.0029.0001.html). The National Meteorological Information Center passed the data set under rigorous quality control procedures (Qian & Lin, 2005). Stations were retained when there was no missing value in the records of any year during this period, giving a total of 603 stations in this study. We used the annual global mean surface temperature (GMST) anomalies relative to 1951–1980 from the National Aeronautics and Space Administration Goddard Institute for Space Studies (http://data.giss.nasa.gov/gistemp/) to characterize the global warming trends (GISTEMP; Hansen et al., 2010; Team, 2016).

2.2. Output of Model Simulations

Output data from historical and future simulations under the +8.5 W/m^2 Representative Concentration Pathway 8.5 (RCP8.5) were retrieved from the Earth System Grid data portal for 20 CMIP5 (phase 5 of the Coupled Model Intercomparison Project) models. We only used RCP8.5 data in this research because these data represent a business-as-usual scenario in which greenhouse gas emissions continue to increase throughout the 21st century (Moss et al., 2010). To maintain consistency among models, only one ensemble member of each model was used (r1i1p1). Models were selected based on the availability of both historical and RCP8.5 simulations for the period 1961–2100. Model outputs were analyzed in their original meshes to preserve the extreme precipitation events produced in GCMs. We only took account of grid boxes covering mainland China and having observation sites (see Table S1 in the supporting information). The monthly GMSTs were used to calculate the annual GMST relative to 1951–1980 from the original resolution for individual model to represent the simulated amount of global warming.

2.3. Analysis of Extreme Values With the *R*-Largest Method

The generalized extreme value (GEV) distribution is a widely used probability function to model and characterize extreme values (e.g., Kharin et al., 2013; W. Li, Jiang, et al., 2017). There are two main approaches for the estimation of GEV parameters (Coles et al., 2001). The first method relies on block maxima series over a period, such as annual maximum daily precipitation for which one maximum value is taken from each year (a block) in the period. The second method relies on extracting the values over a certain (suitably large) threshold from a continuous record such as all values of daily precipitation amount that is above a threshold over a period. It is generally recognized that the peak over threshold method may be able to use the data more efficiently when compared with the block maximum; however, it is difficult to determine the threshold when extreme values are nonstationary. As an extension of the block maxima method, the *R*-largest method uses the *R* number of largest values rather than a single value in the block. It represents a compromise between the block maxima and peak values over threshold. It is a widely used method and shows good performance (Lehmann et al., 2016; Wang & Zhang, 2008; Zhang et al., 2010, 2004).

The GEV distribution can be extended to nonstationary processes, enabling the inclusion of time and other more physically meaningful covariates in its three parameters (location μ, scale σ and shape ξ) (Cheng et al., 2014; Villafuerte & Matsumoto, 2015). Here we consider two types of GEV:

For model GEV0, all the parameters are constant, which implies that no covariate is introduced.

$$\mu(t) = \mu, \sigma(t) = \sigma, \xi(t) = \xi$$

For model GEV1, location and scale parameters are formulated as a function of covariate.

$$\mu(t) = \mu_0 + \mu_1 \,\mathrm{var}(t), \quad \ln\sigma(t) = \ln\sigma_0 + \sigma_1 \,\mathrm{var}(t)$$

In model GEV1, var(*t*) indicates the time series of covariate. We take time as covariate to determine if there is a trend. If GMST is taken as covariate, we can determine if GMST may have influence on extreme values. Extreme precipitation exhibits significant trend when model GEV1 with time being a covariate is selected as the best fitting model determined by the likelihood ratio test. Similarly, extreme precipitation receives a significant influence from global warming if model GEV1 with GMST being a covariate improves the fit. More detailed information can be found in supporting information Text S1.

2.4. Field Significance Test

The extreme value analysis described above is applied for each station or grid box in case of numerical models individually. It is, however, not necessarily very helpful if we consider mitigation policies and climate adaptation plans for a country or region as a whole. In statistics, when a test of significance is conducted at the 5% level, 5% sites are expected to still show statistical significance even if there was no significant trend or GMST has no significant influence on precipitation. Additionally, as there are only a limited number of sites tested and there are potentially correlations among the sites, the percentage of sites showing statistical significance could be larger than this 5% nominal level if there was no significant trend (or influence) over the region (Livezey & Chen, 1983). To determine if a change in extreme precipitation in China, as temporal trend or as response to GMST emerges, we use a field significance test. That is, we consider a change in extreme precipitation detectable if the percentage of sites (stations for observations or grid boxes for model data) showing significant changes is larger than what can be expected from pure chance. It is possible for some sites to have positive trends while other sites negative trends, which results in no net trend. In this case, the statistical test (percentage sites showing significant change) would still indicate field significance and catch the signals. This concept of field significance has been widely used in different regions of the world (Alexander et al., 2006; Kiktev et al., 2003; Westra et al., 2013) but has never been applied to the whole territory of China.

As generally practiced within the framework of field significance, the bootstrap resampling technique is also used here to perform the statistical test. We use 500 samples (or 200 in the case of model simulations) to conduct the probability distribution for our statistical variable (in this case, the percentage of stations showing trend or association with global warming). For each resampling, time series was randomly generated (with replacement), but the resampling time sequences are consistent among stations, ensuring the loss of the temporal sequence, but the preservation of dependencies across space (Westra et al., 2013). If the statistical variable from the initial data lay outside 95% probability distribution obtained by resampling, then the statistical variable is qualified as field significant. More details of the filed significance test are given in supporting information Text S2.

3. Results

Figure 1a shows the spatial distribution of the trend of extreme precipitation in China from 1961 to 2012. The trend is determined by the parameter μ_1 in GEV1. Monitoring stations marked by open blue (red) circles indicate increasing (decreasing) trends. Stations where GEV1 is identified as the best model are represented by solid red (blue) circles indicating significant increasing (decreasing) trends. Figure 1a shows that 60.4% of the stations show an increasing trend and 39.6% show a decreasing trend. The increase is mainly located in South China, whereas the decrease in North China. This structure is consistent with the change in mean precipitation observed in China during this period, which is known as the *flooding in the south and drought in the north* pattern, and is in visual agreement with the study reported by H. X. Li, Chen, et al. (2017). However, the

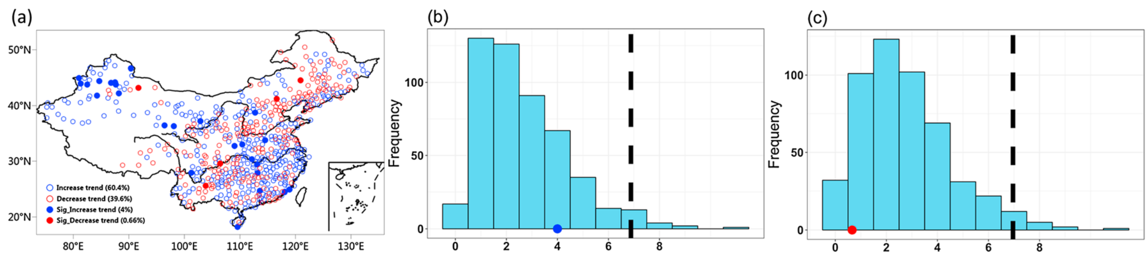

Figure 1. (a) Trend of extreme precipitation during the period 1961–2012 in China. Open blue (red) dots indicate increasing (decreasing) trend. Solid blue (red) dots indicate significant increasing (decreasing) trend at the 5% (two-sided) significance level. (b) Percentage of stations showing a significant increasing trend. The histogram is based on 500 bootstrap samples. The blue solid circle represents results from the original nonpermuted data set. The dashed line marks the 95% probability distribution. (c) The same as (b) but for percentage of stations showing significant decreasing trend; the red solid circle represents results from the original nonpermuted data set.

number of stations with significant trends is relatively small: 4% show a significant increasing trend of extreme precipitation and only 0.66% show a significant decreasing trend, with both trends randomly distributed across the region.

To test whether the significant trend was statistically different from the null hypothesis of random change, the distribution of the percentage of stations showing significant increasing and decreasing trends under the null hypothesis was generated based on the resampling methodology described in section 2.4. Figures 1b and 1c show the number of samples corresponding to the percentage of stations with a significant increasing trend and a significant decreasing trend, respectively. The percentages of stations showing significant increasing and decreasing trends in the original nonpermuted data set are also shown as blue and red dots. The observed percentages are both within the 95% probability evaluated from 500 bootstrap realizations (marked by dashed lines). It is clear that the observed trends in extreme precipitation in China are not significant, implying that an overall trend of extreme precipitation cannot be detected with the current observational record. It is noted that our results are not sensitive to the choice of *R* in *R*-largest method (Figure S1).

We also examined the anthropogenic influence on changes in extreme precipitation by using the GMST as a proxy for anthropogenic change. The relationship between the change in extreme precipitation and the GMST is shown in Figure 2a, which displays the parameter μ_1 deduced from GEV1 with GMST as covariate. Stations showing positive (negative) association of the parameter μ_1 with GMST are mainly located in southern (northern) China. The percentage of stations showing a significant association with the GMST is also small: 5.8% for significant positive associations and 0.66% for significant negative associations. Figures 2b and 2c were obtained in a similar manner as Figures 1b and 1c, but the histogram is now based on the percentage of stations showing a significant association between the location parameter of the GEV and the GMST. It is clear that the observed percentages of stations showing significant positive and negative associations with GMST are well inside the 95% probability distribution in the histogram obtained by resampling, which implies that a significant anthropogenic signal in terms of extreme precipitation change is unlikely to be detectable.

Our results show that a change in extreme precipitation events associated with anthropogenic warming is not detectable within the purely observational framework, although we expect that such an influence will

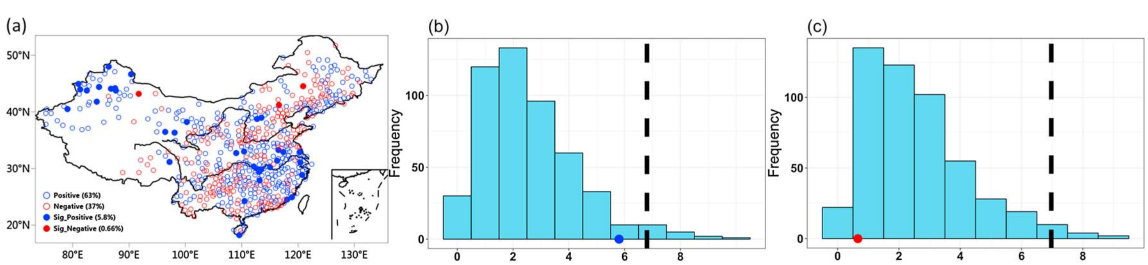

Figure 2. Same as in Figure 1 but for the establishment of relationship between changes in extreme precipitation and the global mean surface temperature (GMST), instead of extreme precipitation trend.

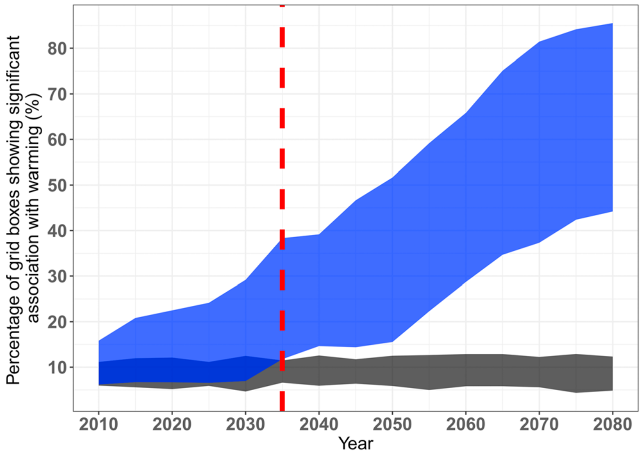

Figure 3. Fraction of grid boxes showing a significant association with the global mean near-surface temperature anomalies (signal, blue) and 95% probability in the distribution constructed with 200 bootstrap resamples (critical value, gray) among models from phase 5 of the Coupled Model Intercomparison Project under Representative Concentration Pathway 8.5 scenario. The leftmost part of the graph shows results for 1961–2010; the calculation was then performed with an accumulative increase of 5 years forward until 1961–2080 at the rightmost end of the graph. The shading indicates the intermodel spread. The red vertical dashed line indicates the time when anthropogenic influence on extreme precipitation is detected for all models.

be detected in the next decades. The main question we address is on the emergence timing of the signal. To do so, we used historical simulations from 1961 to 2005 in the CMIP5 ensemble models and those from 2006 to 2100 under the RCP8.5 scenario. Our calculations, exactly the same as performed previously with the observational data, were applied to each model for different 5-year periods (1961–2010, 1961–2015, and so on, until 1961–2100). Each calculation gave two values in the form of a percentage of model grids over the total number of model grids inside the geographical domain of China for each model. The first value, *S* (signal), is the percentage of model grids showing a significant relationship with global warming. The second percentage, *C* (critical value), is a reference value allowing us to reject or not the null hypothesis of occurrence by pure chance, corresponding to the 95% probability in the distribution constructed with the bootstrap resampling technique. If *S* is larger than *C*, we reject the null hypothesis and adopt the alternative one that anthropogenic signal in extreme precipitation changes could be detected.

A rigorous evaluation of CMIP5 models capability in reproducing rainfall extremes is somehow out of the scope of our current work and has been reported in the literature (e.g., Jiang et al., 2015; Ou et al., 2013). We need, however, to point out that such an evaluation suffers a serious lack of sufficiently dense observation. It is a challenging task to produce high-quality precipitation data to compare with simulations at the spatial scale of models. It is also to be noted that models are self-consistent physically and that different models seem to provide similar results (including the observed spatial pattern and regional average of extreme precipitation, see Figures S2 and S3), which gives us some confidence on models.

Figure 3 shows the results in the form of intermodel spread for the two emblematic percentages *S* and *C*. The leftmost part of the graph shows results from the period 1961–2010, roughly comparable with the observation period 1961–2012. The *S* is largely overlapping with *C*; that is, anthropogenic signal cannot be detected in CMIP5 simulations. This is consistent with observation. The observed *S* (5.8%) and *C* (6.6%) are both basically in the range of CMIP5 models, from 5.9% to 17.2% for *S* and 5.9% to 11.2% for *C*.

The *S* zone increases quickly over time. However, the *C* zone is almost constant. It is noted that the spread among models for *C* may depend on the resolution of models (and thus number of grid boxes in the studied area) and the spatial correlation of data. Anthropogenic signal in extreme changes in precipitation is expected to emerge by around 2035 under RCP8.5 scenario, with a clear separation between the *S* and *C* zones—that is, it is no longer possible to attribute the signal to a random change. This result is consistent with previous studies for East Asia. King et al. (2015) used 23 runs from seven CMIP5 models to study signal of the maximum 1-day precipitation in June-July-August. They concluded that a response to anthropogenic forcing emerges for all models by 2040. However, H. X. Li, Chen, et al. (2017) found an increase in extreme precipitation events over China in recent decades and detected an anthropogenic influence in these events. The discrepancy between these results and our findings may be due to a number of factors, but the use of different data sets may be the main cause. H. X. Li, Chen, et al. (2017) used gridded daily precipitation data at a resolution of $0.25° \times 0.25°$. The region showing a strong increasing trend was northwestern China, where station observations are scarce. There is an issue with the reliability of gridding daily precipitation over this vast region based on sparse observations. Increasing trends from the few observational stations may have been given too large weighting, which may have contributed to the detection of an anthropogenic influence in their study. Our study determined the detectability of an anthropogenic signal based on the percentage of stations at which there is a significant association between precipitation and the global mean temperature. As a consequence, the contribution from a region to the whole country may not be proportional to the size of the region. We recognize that this issue may have effect of reducing the detectability over the whole country if extreme precipitation events truly increase in frequency in unobserved locations. Our approach has a practical implication, however, because it allows us to judge detectability with the current observational network.

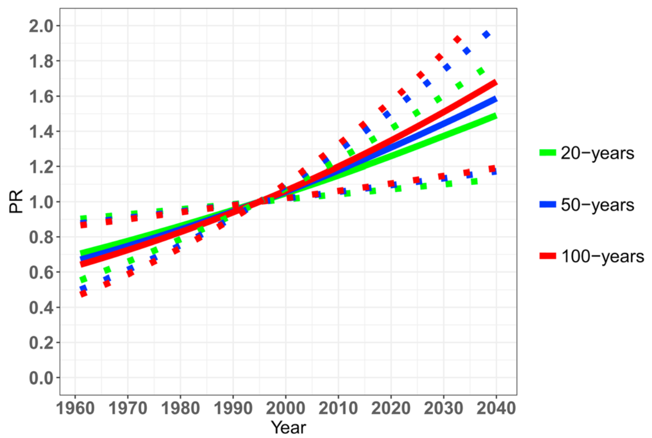

Figure 4. Temporal evolution of the probability ratio (PR) for extreme events with return period of 20, 50, and 100 years in the historical period (1995, centered year for 1986–2005). Solid lines indicate the multimodel ensemble average, and the two corresponding dotted lines (same colors) represent the intermodel spread.

Based on results from model GEV1 (taking *t* as the covariate for the location and scale parameters), we use now the concept of probability ratio (PR) to measure the risk change for a given extreme event (as threshold). It is defined as the ratio of the probability in the changing climate to that of the reference period, 1986–2006 (centered year is 1995). With GEV1 parameters known, we can calculate the PR for whatever the time is (provided that it is in a reasonable range). In term of extreme events, we select events corresponding to return period of 20, 50, and 100 years in the reference climate. These return periods are estimated for individual grids and models separately. Figure 4 shows results with a temporal evolution (from 1961 to 2040) of the PR averaged over China for the three return periods. As expected, PR is equal to 1.0 in 1995 (the reference year). It becomes larger (less) than 1.0 after (before) 1995. The risk of extreme precipitation increases with time, especially for rarer events (longer return periods). The most intense and rarest extreme events have the largest increase in risk. By 2035, the probability of 20-, 50-, and 100-year events in the reference climate increases by a factor of 1.4, 1.5, and 1.6, respectively. This implies that regional events expected to occur once every 20, 50, and 100 years in the current climate (1995) are expected to occur every 15, 34, and 63 years when the anthropogenic signal clearly emerges in climate models by 2035. Model uncertainties increase with time, with a greater uncertainty for rarer events.

4. Conclusions

We used statistical methods based on field significance to estimate the time horizon when the anthropogenic signal of extreme precipitation would emerge over China. The historical and future RCP8.5 scenario simulations from CMIP5 models were used, together with data from the Chinese meteorological network. We conducted the present study with the aim of providing useful information for the design and implementation of adaptation measures. Our conclusions are as follows:

1. Changes in extreme precipitation events represented by the annual maximum 1-day precipitation may still be too small to be detectable against natural variability over China within the observational record. The limited sample size may add uncertainty in the field significance test, but we tend to conclude that a significant anthropogenic influence on extreme precipitation events in China may not yet have emerged.
2. Within the framework of the CMIP5 ensemble models, the anthropogenic signal of changes in extreme precipitation would become significantly detectable by around 2035, in the sense that the signal is well separated from the background noise. As it is difficult to compare extreme precipitation in the simulations and in the observations due to mismatch in spatial scale, the time of emergence of climate change signal in the real world may still differ.
3. Changes in extreme precipitation events become important when they are detectable at the time horizon of the emergence of an anthropogenic signal. Regional events expected once every 20, 50, and 100 years in the current climate will occur every 15, 34, and 63 years when the anthropogenic signal clearly emerges.

It should be noted that uncertainties due to different emission scenarios are relatively low over China before 2040s (Chen & Sun, 2015). Similar results are therefore obtained when using the future RCP4.5 scenario instead of RCP8.5 (Figure S4).

Finally, we want to point out that our study also raises new challenges. As anthropogenic influence cannot be detected with a different treatment of observational data and as human influence is not detected in parts of CMIP5 models, the robustness of detecting anthropogenic influence in historical observation and modeling requires further studies.

Acknowledgments
We acknowledge the World Climate Research Programme's Working Group on Coupled Modeling and the modeling groups listed in Table S1 for making their simulations available for analysis and the Program for Climate Model Diagnosis and Interpretation for collecting and archiving the CMIP5 model output (http://esgf.llnl.gov.). This work is supported by the National Key Research and Development Program of China (Grant 2017YFA0603804), National Natural Science Foundation of China (41675081) and the China Scholarship Council (CSC) under the State Scholarship Fund. L. Li was partly supported by the French ANR (Project China-Trend-Stream).

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