Attribution of the Extreme Drought-Related Risk of Wildfires in Spring 2019 over Southwest China

Jizeng Du, Kaicun Wang, Baoshan Cui

The 2019 extreme wildfire in South China was largely related to both anthropogenic warming and El Niño event. They increased the weather-related risk of extreme wildfire by 7.2 times and 3.6 times, respectively.

AFFILIATIONS: Du and Cui—State Key Joint Laboratory of Environmental Simulation and Pollution Control, School of Environment, Beijing Normal University, Beijing, China; Wang—College of Global Change and Earth System Science, Beijing Normal University, Beijing, China

CORRESPONDING AUTHOR: Kaicun Wang, kcwang@bnu.edu.cn

DOI:10.1175/BAMS-D-20-0165.1

A supplement to this article is available online (10.1175/BAMS-D-20-0165.2)

©2021 American Meteorological Society
For information regarding reuse of this content and general copyright information, consult the [AMS Copyright Policy](#).

From March to May 2019, the total precipitation in southwest China (21°–29°N, 98°–105°E) was less than half of the historical average and was the lowest since 1960. Moreover, the air temperature was approximately 1.6°C warmer than the historical average since 1960, leading to the daily maximum temperature reaching or breaking historical records in more than 24 cities in southwest China (Zeng et al. 2020). Higher temperatures and reduced precipitation led to severe meteorological drought, which notably reduced agricultural production and increased the forest fire risk in the region (Ding and Gao 2020). In particular, a lightning-caused forest fire in Muli County killed 31 firefighters and burned about 30 ha of forest (Li 2019; Liu et al. 2020).

Consistent with global warming, southwest China has warmed, and precipitation has declined, resulting in a significant drought trend in this region, especially after

2000 (Ma et al. 2017; M. Zhang et al. 2013). An El Niño phase started in September 2018 and lasted until June 2019. The northwestern Pacific subtropical high (NWPSH) strengthened, with an anomalously strong anticyclone appearing near the Philippines. At same time, the Tibetan Plateau high moved eastward and caused abnormal downward airflows in southwest China, which blocked moisture convergence from the Bay of Bengal to this region. As a result, the lower precipitation with a higher temperature caused severe drought in spring 2019, thus greatly increasing the risk of forest fires in southwest China (Lin et al. 2015; Zhang and Zhou 2015; W. Zhang et al. 2013).

It is important to explore how anthropogenic contribution to the risk of forest fire in the context of changing climate (Di Virgilio et al. 2019; Dupuy et al. 2020). Here, based on daily meteorological observations and the fire weather index (FWI) risk model, we quantified the impacts of anthropogenic factors and El Niño events on the weather-related forest fire risk in southwest China.

Dataset and method.

The study region (21°–29°N, 98°–105°E) encompasses the spatial extent of extreme drought in the spring of 2019, and it includes Yunnan Province and the southern portion of Sichuan Province (see Fig. ES1 in the online supplemental material; <https://doi.org/10.1175/BAMS-D-20-0165.2>). This region is an important forest region in Southwest China with complex terrain, thus making it difficult to control and fight forest fires. The spring (March–May) is the season with a high risk of wildfires in the study region, with more than half of the total number of fires in the whole year occurring during the spring seasons (Tian et al. 2010).

The daily observations from 1960 to 2019 at 31 meteorological stations in this region were obtained from the China Meteorological Data Service Center (<http://data.cma.cn/en>) (see Fig. ES1). The map of land cover in 2010 with a 1-km resolution (<http://glc30.tianditu.com/>) was used to extract the forest areas. The MODIS Thermal Anomalies and Fire product (MOD14A2, <https://modis.gsfc.nasa.gov/>) was used to obtain a time series of spatial fire records during the period from 2001 to 2019. This product has an 8-day temporal resolution and a 1-km spatial resolution, and each pixel is a maximum composite of the level-2 pixel classes for the 8-day period (de Klerk 2008).

The FWI system developed based on forest regions in Canada is used to assess the weather conditions for the risk of forest fires (de Groot 1987), which has been found to be suitable for variable regions including Europe and China (Satir et al. 2016; Tian et al. 2014; Tian et al. 2011). The FWI system evaluates the risk of forest fires based on six components that provide information about fuel, moisture, the rate of fire spread, fuel consumption and the fire intensity. All FWI system components were calculated based on the measured daily air temperature (T_a), minimum relative humidity (RH_{min}), wind speed (WS), and daily total precipitation (P) (see also the online supplementary material).

The persistent high FWI event is defined as the maximum average FWI over three consecutive months in each year (hereafter FWI_{x3m}). We selected neutral years (including La Niña years) and El Niño years from the FWI time series of both observations and simulations based on the Niño-3.4 index, which reflects the average equatorial sea surface temperature (SST) anomaly across the Pacific (5°N–5°S, 170°W–120°W). El Niño events are defined when the Niño 3.4 index exceeds 0.4°C for a period of 6 months or more (Bunge and Clarke 2009; Smith et al. 2008).

Taking observation as a reference, we used a quantile-matching algorithm to adjust the climate variables of simulations from HadGEM3-A-based attribution system (hereafter called HadGEM3-A) and CMIP6 before the attribution process (Christidis et al. 2013; Ciavarella et al. 2018; Eyring et al. 2016). A detailed description of the adjustment procedure was given by Wang et al. (2010). We used the Kolmogorov–Smirnov (K-S) test to select the model simulations whose all-forcings simulations have no significant difference with observation in probability distribution of FWI. Based on above criteria

($p > 0.1$), there are 15 simulations from HadGEM3A during the period of 1960–2015 (56×15 samples). There are 27 simulations from 9 models from CMIP6 during 2009–29 (20×27 samples), assuming similar climate condition to 2019. Historical simulations with all-forcings (ALL; 2009–14) were combined with corresponding shared socioeconomic pathway (SSP) 2–4.5 scenarios (2015–29). The corresponding natural-forcings-only simulations (NAT) from CMIP6 were selected from 1960 to 2014 (55×27 samples).

Based on the simulations mentioned above, we constructed the distribution of FWI_{x3m} in ALL and NAT, and estimated the occurrence probability and return periods of the extreme FWI_{x3m} greater than that in 2019 with/without anthropogenic forcings. Then, we compared the difference in the likelihood between ALL and NAT to determine the anthropogenic warming on the extreme FWI events.

Generalized extreme value (GEV) distribution is a flexible three-parameter distribution, which can provide a conservative estimation of the probability and return period for extreme events based on observations or model simulations (Huang et al. 2016; Jenkinson 1955). Here, GEV distribution was then applied to the time series of FWI_{x3m} in the two scenarios with stationary climate, including neutral years with natural forcings only and El Niño years with natural forcings only. The scenarios with all forcings are not stationary climates, and their mean is not representative of 2019. So the scaled GEV distributions are determined to fit the FWI_{x3m} in scenarios with all forcings (see the online supplemental material). The sample size of the four scenarios are shown in Table ES1.

The likelihoods of FWI_{x3m} with anomalies above that in 2019 were estimated in every scenario (Coles et al. 2001). Additionally, the fraction of attributable risk (FAR) and the corresponding probability ratio (PR) were used to estimate the effects of the anthropogenic warming and El Niño events (Stott et al. 2016). Sampling uncertainty was estimated using a Monte Carlo bootstrap procedure with replacement, and this procedure was run 1,000 times for all ensemble members in the individual scenarios (Christidis et al. 2013).

Results.

Observed extreme FWI in the spring of 2019. As shown in Fig. 1a, during spring 2019, the surface air temperature was 1.54°C higher (the second-highest temperature) than the historic value, and the precipitation was 1.19 mm day^{-1} less than that in the same period historically (the lowest since 1960). The total precipitation in this region decreased by 57.8% relative to the multiyear mean value for the spring season. The high temperature and low precipitation resulted in a severe meteorological drought in this region (see Fig. 1b).

We used the FWI as an indicator of forest fire risk in the study region. As shown in Fig. 1c, the FWI performed reasonably in estimating the forest fire risk. The correlation coefficient between the FWI and the density of forest fire points was 0.662 ($p < 0.05$; see Fig. 1c). Based on the records from 1960 to 2019, the regional mean March–May FWI was 12.31 in 2019, which was 93.5% higher than the contemporaneous multiyear average and the third-highest value in recorded history (see Fig. 1d). Forest fire areas in 2019 showed a marked upturn compared with the previous years since 2014. However, the density of forest fire points in 2019 was not significantly higher than that in other years, possibly due to the government's increased efforts to prevent forest fires in the region (Xiong et al. 2020; Zhai et al. 2018).

As shown in Figs. 2a and 2b, according to the fitted curve of scaled GEV distribution, the return periods of high T_a and low P in spring 2019 were 53 and 90 years, respectively. The return period of the FWI_{x3m} in this period was 51 years (see Fig. 2c). Based on the FWI system, we quantified the contribution of individual variables to extreme FWI and the method was introduced in supplementary material (Du et al. 2019). The anomalies of T_a and P were the main driving factors of the FWI_{x3m} in 2019, accounting for 36.8% and 29.7% of the trend, respectively. The contributions of $\text{RH}_{\min}$

Fig. 1. (a) Time series of March–May daily mean precipitation (P ; blue) and air temperature (T_a ; red) in southwest China; P and T_a are expressed as anomalies relative to the 1970–2000 mean. **(b)** The anomalies of total precipitation [ATP = $(P_i - \bar{P})/\bar{P}$] are calculated based on the total precipitation (P_i) from March to May (MAM; defined as spring) and March–May precipitation ($\bar{P}$) between 1960 and 2018 in China. **(c)** The fire weather index and the density of forest fire points in spring in Southwest China were significantly correlated at the 95% confidence level ($R = 0.663$). **(d)** Time series of the March–May FWI (yellow) and the density of forest fire points in spring in southwest China (green).

and WS were relatively small, accounting for only 11.5% and 5.3% of the overall effect, respectively (see Fig. 2d).

As shown in Fig S3, FWI_{x3m} had a significant positive correlation with Niño 3.4 ($p < 0.05$), which indicates El Niño may increase the likelihood of extreme FWI_{x3m} . Therefore, we selected two groups from the time series of observations: one for detrended El Niño years (18 samples) with only the effect of El Niño events considered and the other for neutral years (42 samples) with only the effects of the long-term trend of climate variables considered. As shown in Fig. 2a and 2b, the likelihood of observing extreme T_a and P was much higher in El Niño years than in neutral years. Therefore, the likelihood of 2019 FWI_{x3m} during El Niño years was higher than that during neutral years (Fig. 2c). Note that the relationship between El Niño and FWI_{x3m} is sensitive to the occurrence time, duration, and magnitude of El Niño (see Fig S3). Hence, we only estimate the average effect of all El Niño events during 1960–2019.

During neutral years, the contribution of T_a was much higher than that of P , with values of 54.1% and 14.6%, respectively. However, during the El Niño phase, the contribution of P to the extreme FWI_{x3m} in 2019 was 40.2%, which was higher than that of T_a at 25.3% (see Fig. 2d). Therefore, long-term trends in regional climate mainly increase the likelihood of extreme FWI by increasing temperature, and El Niño events mainly increase the likelihood of extreme FWI by both reducing precipitation and increasing air temperature (see Table 1). Other climate variables and the interaction among variables have little effect on the extreme FWI (5.1%–16.3%).

FIG. 2. (a) Return periods for the mean air temperature (T_a) with FWI_{x3m} based on the observations in all years, El Niño years, and neutral years from 1960 to 2019. The color dashed lines denote the 95% confidence intervals. The crosses are estimated from the empirical distributions of the observed T_a with the black dashed line denoting the observed T_a with FWI_{x3m} in 2019. (b) As in (a), but for precipitation (P). (c) As in (a), but for the FWI_{x3m} . (d) The contributions of T_a , P , daily minimum relative humidity (RH_{min}), wind speed (WS), and the interaction among variables (E_n) to the likelihood of the extreme FWI_{x3m} in 2019. The whiskers show the 95% confidence intervals.

Attribution analysis based on simulations. According to the HadGEM3A attribution system, we found that the likelihood of occurrence of the 2019 FWI_{x3m} anomaly under all forcings was 7.21 times (95% CI: 1.64–12.93) that under natural forcings only (see Fig. 3a). El Niño events increased the likelihood of the 2019 FWI_{x3m} anomaly by 3.57 times (95% CI: 1.32–10.02). The compound anthropogenic and El Niño effects resulted

Table 1. Statistics (mean plus and minus standard deviation) of climate variables and FWI in the study area from 1960 to 2018, which are classified based on different phases of ENSO, including El Niño years and neutral years.

Variables	El Niño years (18 samples)	Neutral years (42 samples)
T_a (°C)	0.270 ± 0.601	−0.076 ± 0.554
P (mm day ^{−1})	−2.041 ± 1.76	0.712 ± 4.899
RH_{min} (%)	−1.263 ± 1.015	0.369 ± 2.656
Win (km h ^{−1})	0.510 ± 1.789	−0.155 ± 2.22
FWI	0.345 ± 3.542	−0.125 ± 2.493

Fig. 3. (a) Probability density of FWI_{x3m} estimated from HadGEM3A for the all-forcings (ALL; red) and natural-forcing-only (NAT; blue) simulations during 1960–2013. The best estimate is marked by the solid lines, and the thick black line is the FWI_{x3m} in 2019 over the study region. (b) Scaled GEV fits 2019 (color solid lines) for FWI_{x3m} from 1960 to 2013 based on the HadGEM3A simulations during El Niño years (red) and neutral years (blue) under ALL. The crosses are estimated from the empirical distributions of the simulated FWI_{x3m} with the black dashed line denoting the 2019 extreme FWI_{x3m} . (c) As in (b), but for NAT. (d) The fraction of attributable risk (FAR) and corresponding probability ratios (PR) calculated using different scenario combinations. The bars show the interquartile range (5th–95th percentiles), and the asterisks indicate the best estimates for the fraction of attributable risk.

in a 21.4-fold (95% CI: 8.1–35.9) increase in the risk of the extreme FWI experienced in spring 2019 (see Figs. 3b–d).

According to the CMIP6 experiments, the likelihood of the 2019 extreme FWI_{x3m} under ALL was 17.39 times (95% CI: 7.42–26.83) that under NAT (see Figs. ES5a). El Niño years increased the likelihood of the extreme FWI_{x3m} by 3.11 times (95% CI: 1.63–6.29) higher than that in neutral years. Anthropogenic warming and El Niño together resulted in a 37.2-fold (95% CI: 5.45–81.3) increase in the likelihood of 2019 extreme FWI_{x3m} (see Figs. ES5b–d).

Note that there may be complicated relationship between anthropogenic climate change and El Niño events, namely, that the influence of El Niño on the extreme FWI_{x3m} is partly due to the indirect effects of anthropogenic climate change. However, how El Niño amplitude and frequency respond to anthropogenic warming is important while has been no consensus on it (Cai et al. 2015; Collins et al. 2010; Kim et al. 2014). The uncertainty of attribution analysis is sensitive to the synergy effect of anthropogenic warming with El Niño events in global scale, as well as the performance of FWI model and attribution system.

Conclusions.

According to the analysis of observational data, both El Niño events and human-induced climate change are driving factors of extreme FWI. The human-induced climate change exacerbate the likelihood of extreme FWI by increasing T_a , and El Niño events increase the likelihood of extreme FWI by both reducing P and increasing T_a . Based on observations, El Niño events significantly increased the risk of extreme FWI in spring 2019 (Fig. 2c).

Furthermore, we quantify the effect of anthropogenic warming on the extreme FWI event. The simulation experiments of HadGEM3A (CMIP6) showed that anthropogenic warming increased the likelihood of the extreme $\text{FWI}_{3\text{mm}}$ in 2019 by 7.21 (17.39) times. El Niño events increased the likelihood of the extreme $\text{FWI}_{3\text{mm}}$ in 2019 by 3.57 (3.11) times. Combined, anthropogenic warming and El Niño events may result in a more than 21-fold (21.4–37.2 times) increase in the likelihood of occurrence of an extreme $\text{FWI}_{3\text{mm}}$.

Acknowledgments. This study was funded by the National Basic Research Program of China (2018YFC1507701 and 2017YFA0603601), the Fundamental Research Funds for the Central Universities (2019NTST10), and the National Natural Science Foundation of China (42005019). The Met Office for the HadGEM3-A-based attribution system (<http://catalog.ceda.ac.uk/>) and the World Climate Research Programme's Working Group on Coupled Modeling (<http://cmip.pcmi.llnl.gov/cmip6/>) for the model simulations.

References

- Bunge, L., and A. J. Clarke, 2009: A verified estimation of the El Niño index Niño-3.4 since 1877. *J. Climate*, **22**, 3979–3992, <https://doi.org/10.1175/2009JCLI2724.1>.
- Cai, W., and Coauthors, 2015: ENSO and greenhouse warming. *Nat. Climate Change*, **5**, 849–859, <https://doi.org/10.1038/nclimate2743>.
- Christidis, N., and Coauthors, 2013: A new HadGEM3-A-based system for attribution of weather and climate-related extreme events. *J. Climate*, **26**, 2756–2783, <https://doi.org/10.1175/JCLI-D-12-00169.1>.
- Ciavarella, A., and Coauthors, 2018: Upgrade of the HadGEM3-A based attribution system to high resolution and a new validation framework for probabilistic event attribution. *Wea. Climate Extremes*, **20**, 9–32, <https://doi.org/10.1016/j.wace.2018.03.003>.
- Coles, S., J. Bawa, L. Trenner, and P. Dorazio, 2001: An Introduction to Statistical Modeling of Extreme Values. Springer, 209 pp.
- Collins, M., and Coauthors, 2010: The impact of global warming on the tropical Pacific Ocean and El Niño. *Nat. Geosci.*, **3**, 391–397, <https://doi.org/10.1038/ngeo868>.
- de Groot, W. J., 1987: Interpreting the Canadian forest fire weather index (FWI) system. Proc. Fourth Central Region Fire Weather Committee Scientific and Technical Seminar, Winnipeg, MB, Canada, Canadian Forest Service, 3–14, <https://webcache.googleusercontent.com/search?q=cache:XJ-Hi2fANSUJ:https://cfs.nrcan.gc.ca/publications%3Fid%3D23688+&cd=1&hl=en&ct=clnk&gl=in>.
- de Klerk, H., 2008: A pragmatic assessment of the usefulness of the MODIS (Terra and Aqua) 1-km active fire (MOD14A2 and MYD14A2) products for mapping fires in the fynbos biome. *Int. J. Wildland Fire*, **17**, 166–178, <https://doi.org/10.1071/WF06040>.
- Ding, T., and H. Gao, 2020: The record-breaking extreme drought in Yunnan Province, Southwest China during spring and early summer of 2019 and possible causes. *J. Meteor. Res.*, **34**, 997–1012, <https://doi.org/10.1007/s13351-020-0032-8>.
- Di Virgilio, G., J. P. Evans, S. A. Blake, M. Armstrong, A. J. Dowdy, J. Sharpley, and R. McRae, 2019: Climate change increases the potential for extreme wildfires. *Geophys. Res. Lett.*, **46**, 8517–8526, <https://doi.org/10.1029/2019GL083699>.
- Du, J., K. Wang, S. Jiang, B. Cui, J. Wang, C. Zhao, and J. Li, 2019: Urban dry island effect mitigated urbanization effect on observed warming in China. *J. Climate*, **32**, 5705–5723, <https://doi.org/10.1175/JCLI-D-18-0712.1>.
- Dupuy, J., and Coauthors, 2020: Climate change impact on future wildfire danger and activity in southern Europe: A review. *Ann. For. Sci.*, **77**, 35, <https://doi.org/10.1007/s13595-020-00933-5>.
- Eyring, V., S. Bony, G. A. Meehl, C. A. Senior, B. Stevens, R. J. Stouffer, and K. E. Taylor, 2016: Overview of the Coupled Model Intercomparison Project phase 6 (CMIP6) experimental design and organization. *Geosci. Model Dev.*, **9**, 1937–1958, <https://doi.org/10.5194/gmd-9-1937-2016>.
- Huang, W. K., M. L. Stein, D. J. McInerney, S. Sun, and E. J. Moyer, 2016: Estimating changes in temperature extremes from millennial-scale climate simulations using generalized extreme value (GEV) distributions. *Adv. Stat. Climatol. Meteor. Oceanogr.*, **2**, 79–103, <https://doi.org/10.5194/ascmo-2-79-2016>.
- Jenkinson, A. F., 1955: The frequency distribution of the annual maximum (or minimum) values of meteorological elements. *Quart. J. Roy. Meteor. Soc.*, **81**, 158–171, <https://doi.org/10.1002/qj.49708134804>.
- Kim, S. T., W. Cai, F.-F. Jin, A. Santoso, L. Wu, E. Guilyardi, and S.-I. An, 2014: Response of El Niño sea surface temperature variability to greenhouse warming. *Nat. Climate Change*, **4**, 786–790, <https://doi.org/10.1038/nclimate2326>.
- Li, Q., 2019: Causes of forest fires and prevention and control measures—A case study of “3.30” fire in Muli county. *Sichuan Linye Keji*, **40**, 108–111, <https://doi.org/10.16779/j.cnki.1003-5508.2019.04.022>.

- Lin, W., C. Wen, Z. Wen, and H. Gang, 2015: Drought in Southwest China: A review. *Atmos. Ocean. Sci. Lett.*, **8**, 339–344, <https://doi.org/10.3878/AOSL20150043>.
- Liu, Y., J. Zhu, X. Shao, N. C. Adusumilli, and F. Wang, 2020: Diffusion patterns in disaster-induced internet public opinion: Based on a Sina Weibo online discussion about the ‘Liangshan fire’ in China. *Environ. Hazards*, <https://doi.org/10.1080/17477891.2020.1758608>, in press.
- Ma, S., T. Zhou, O. Angéilil, and H. Shiogama, 2017: Increased chances of drought in southeastern periphery of the Tibetan Plateau induced by anthropogenic warming. *J. Climate*, **30**, 6543–6560, <https://doi.org/10.1175/JCLI-D-16-0636.1>.
- Satir, O., S. Berberoglu, and C. Donmez, 2016: Mapping regional forest fire probability using artificial neural network model in a Mediterranean forest ecosystem. *Geomatics Nat. Hazards Risk*, **7**, 1645–1658, <https://doi.org/10.1080/19475705.2015.1084541>.
- Smith, T. M., R. W. Reynolds, T. C. Peterson, and J. Lawrimore, 2008: Improvements to NOAA’s historical merged land–ocean surface temperature analysis (1880–2006). *J. Climate*, **21**, 2283–2296, <https://doi.org/10.1175/2007JCLI2100.1>.
- Stott, P. A., and Coauthors, 2016: Attribution of extreme weather and climate-related events. *Wiley Interdiscip. Rev.: Climate Change*, **7**, 23–41, <https://doi.org/10.1002/wcc.380>.
- Tian, X., F. Zhao, L. Shu, and M. Wang, 2010: Hotspots from satellite monitoring and forest fire weather index analysis for southwest China. *For. Res.*, **23**, 523–529.
- , L. Shu, F. Zhao, M.-y. Wang, and D. J. McRae, 2011: Future impacts of climate change on forest fire danger in northeastern China. *J. For. Res.*, **22**, 437–446, <https://doi.org/10.1007/s11676-011-0185-5>.
- , F. Zhao, L. Shu, and M.-y. Wang, 2014: Changes in forest fire danger for south-western China in the 21st century. *Int. J. Wildland Fire*, **23**, 185–195, <https://doi.org/10.1071/WF13014>.
- Wang, X. L., H. Chen, Y. Wu, Y. Feng, and Q. Pu, 2010: New techniques for the detection and adjustment of shifts in daily precipitation data series. *J. Appl. Meteor. Climatol.*, **49**, 2416–2436, <https://doi.org/10.1175/2010JAMC2376.1>.
- Xiong, Q., and Coauthors, 2020: Fire from policy, human interventions, or biophysical factors? Temporal–spatial patterns of forest fire in southwestern China. *For. Ecol. Manage.*, **474**, 118381, <https://doi.org/10.1016/j.foreco.2020.118381>.
- Zeng, H., C. Xiao, X. Chen, Y. Chen, and D. Ye, 2020: State of China’s climate in 2019. *Atmos. Ocean. Sci. Lett.*, **13**, 356–362, <https://doi.org/10.1080/16742834.2020.1762159>.
- Zhai, H., X. Wei, P. Zhao, and Y. Chen, 2018: The situation analysis of forest fire control in China. *Linchan Gongye*, **45**, 43–48.
- Zhang, L., and T. Zhou, 2015: Drought over East Asia: A review. *J. Climate*, **28**, 3375–3399, <https://doi.org/10.1175/JCLI-D-14-00259.1>.
- Zhang, M., J. He, B. Wang, S. Wang, S. Li, W. Liu, and X. Ma, 2013: Extreme drought changes in Southwest China from 1960 to 2009. *J. Geogr. Sci.*, **23**, 3–16, <https://doi.org/10.1007/s11442-013-0989-7>.
- Zhang, W., F.-F. Jin, J.-X. Zhao, L. Qi, and H.-L. Ren, 2013: The possible influence of a nonconventional El Niño on the severe autumn drought of 2009 in Southwest China. *J. Climate*, **26**, 8392–8405, <https://doi.org/10.1175/JCLI-D-12-00851.1>.