Probabilistic Heat Wave Forecast Based on a Large-Scale Circulation Pattern Using the TIGGE Data

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(Manuscript received 16 September 2019, in final form 23 December 2019)

ABSTRACT

Forecasting extreme events is important for having more time to prepare and mitigate high-impact events because those are expected to become more frequent, intense, and persistent around the globe in the future under the warming atmosphere. This study evaluates the probabilistic predictability of the heat wave index (HWI) associated with large-scale circulation patterns for predicting heat waves over South Korea. The HWI, reflecting heat waves over South Korea, was defined as the vorticity difference at 200 hPa between the South China Sea and northeast Asia. The forecast of up to 15 days from five ensemble prediction systems and the multimodel ensemble has been used to predict the probabilistic HWI during the summers of 2011–15. The ensemble prediction systems consist of different five operational centers, and the forecast skill of the probability of heat waves occurrence was assessed using the Brier skill score (BSS), relative operating characteristics (ROC), and reliability diagram. It was found that the multimodel ensemble is capable of better predicting the large-scale circulation patterns leading to heat waves over South Korea than any other single ensemble system through all forecast lead times. We concluded that the probabilistic forecast of the HWI has promise as a tool to take appropriate and timely actions to minimize the loss of lives and properties from imminent heat waves.

1. Introduction

Forecasts of extreme weather events are important for having more time to prepare and mitigate their adverse impacts such as heat wave, droughts, heavy rain, and floods. Policy makers need accurate and timely prediction information of these high-impact events to reduce socioeconomic risks and to effectively respond in advance. In particular heat waves are expected to become more frequent, intense, and persistent across the globe in the future under the warming atmosphere (Meehl and Tebaldi 2004; Oliver et al. 2018).

Many studies have analyzed the mechanism of heat waves, which bring both the risk of heat-related health problems and economic costs (Guirguis et al. 2014; Teng et al. 2013). Most extreme temperature events are associated with large-scale atmospheric circulation patterns. In eastern North America, Europe, and western Asia surface temperatures have been substantially raised by regional circulation patterns that are associated with

atmospheric blocking since 1979 (Horton et al. 2015; Galarneau et al. 2012; Schneidereit et al. 2012). Chen and Lu (2016) suggested the important role of the large-scale circulations in causing temperature extremes in western North China. Because high-impact weather events are largely dependent on the large-scale atmospheric circulation, a better understanding of it could reduce the uncertainty of future projections and improve of the predictability of high-impact weather heat wave events (Pezza et al. 2012; Grotjahn et al. 2016). Lee and Lee (2016), for instance, found the dominant mechanisms associated with South Korea heat waves at a national or greater spatial scale by regressing the leading principal component of heat wave frequency with a large-scale atmospheric circulation, and thereby identified a north–south dipole pattern between the South China Sea and northeast Asia.

While dynamic models have been widely used to predict these high-impact weather events, the associated uncertainty is considerable and tends to increase with lead time (Lorenz 1963). Since, deterministic weather forecasts have limitations for policy makers

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DOI: 10.1175/WAF-D-19-0188.1

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to design early warning systems, ensemble prediction systems have been rapidly developed for in particular short- (beyond 12 h and up to 3 days) and medium- (beyond 3 days and up to 10 days) range lead times. Consequently, multimodel prediction systems and probabilistic predictions were developed to reduce the systematic and random errors in individual model formulations (Doblas-Reyes et al. 2000; Fritsch et al. 2000; Stephenson and Doblas-Reyes 2000; Kharin and Zwiers 2003; Peng et al. 2002; Palmer et al. 2004).

Lalaurette (2003), for example, indicates that the severe heat waves in Europe could be predicted up to 5 days in advance with the European Centre for Medium-Range Weather Forecasts (ECMWF) ensemble prediction system. Bao et al. (2011) showed that a single model ensemble system often failed to reproduce specific atmospheric conditions related to flood and drought. Even though multimodel and probabilistic prediction systems have been rapidly developed and their forecast skills have appreciably increased, there is still room for further improvement of forecasting high-impact weather due to limitations of state-of-the-art climate models in predicting the extreme conditions (Weisheimer et al. 2011). Thus, the World Meteorological Organization's (WMO) World Weather Research Programme (WWRP) established The Observing System Research and Predictability Experiment (THORPEX) Interactive Grand Global Ensemble (TIGGE) in 2003 (Bougeault et al. 2010). A key component of this project is to accelerate improvements in forecasting high-impact weather with lead times from 1 day to 2 weeks. Although forecasts of heat waves (onset, maintenance, decay) are potentially beneficial across a broad range of application sectors including health, agriculture, infrastructure, energy, and emergency services, previous studies of heat wave predictions have been limited to several case studies. For example, Matsueda (2011) investigated the predictability of the blocking-induced extreme surface temperatures such as the Russian 2010 heat wave. Teng et al. (2013) showed that the heat waves over the United States were preceded by 15–20 days by the specific atmospheric circulation pattern based on ensemble atmospheric model simulations. Hudson et al. (2011) evaluated the predictability of the heat waves over Australia in 2009 at the subseasonal scale.

To the best of our knowledge, however, few studies have been conducted for real-time prediction of heat waves using a probabilistic multimodel ensemble system in a medium range (forecast lead time from 3 to 10 days). The probabilistic information may provide more benefits than deterministic forecasts for practical decision-making for providing accurate early warning of high-impact weather events. As a case study, here we assessed the

probabilistic predictability of heat wave occurrence over South Korea using a heat wave index (HWI) associated with large-scale circulations based on ensemble prediction systems from multiple operational centers for the summers of 2011–15.

2. Data and methodology

a. TIGGE data and observation data

This study used the prediction datasets obtained from TIGGE, through the ECMWF portal (<https://www.ecmwf.int/en/research/projects/tigge>). THORPEX was established in 2003 by the WMO as a 10-yr international global atmospheric research and development program. It aimed to accelerate improvements in 1 day–2 weeks forecast skills for high-impact weather forecasts through enhancing atmospheric observations (Bougeault et al. 2010; Swinbank et al. 2016). The TIGGE portal provides 10 ensemble system datasets to develop societal and economic applications for regional climate prediction and probabilistic forecasting applied to health, agriculture, or energy managements. We used the ensemble prediction data for geopotential height at 500 hPa, zonal wind at 200 hPa, meridional wind at 200 hPa, daily maximum temperature for the period of 1 June–31 August from 2011 to 2015 from five numerical weather prediction (NWP) centers: the ECMWF, the Met Office (UKMO), the Canadian Meteorological Centre (CMC), the Korea Meteorological Administration (KMA), and the National Centers for Environmental Prediction (NCEP) in the United States. These NWP centers were selected by considering the study periods, the availability of required variables, and the number of ensemble members. The key characteristics of the ensemble systems selected in this analysis, such as forecast length, initial perturbation of model, resolution, and the number of ensembles, are listed in Table 1.

The temperature observation data at 60 stations in South Korea were also collected to analyze the occurrence of heat wave events in South Korea. Typically, a heat wave is defined as a duration criterion of an excessive threshold (Robinson 2001). However, the duration criteria of an excessive threshold are defined in various ways across the world, depending on regional climate, among other factors. In South Korea, a heat wave watch and warning system was launched in 2007. A heat watch is issued when the daily maximum temperature is expected to reach or exceed to 33°C for more than two consecutive days, and a warning is issued when daily maximum temperatures exceed 35°C for 2 consecutive days or longer. In this study, the excessive threshold was defined as 33°C, the 90th percentile temperature for the period of June–August. In addition, the heat waves

TABLE 1. Descriptions of TIGGE models used in this study.

Country/center	Forecast length	Initial perturbation	Model resolution	Ensemble members
United States/NCEP	15 days	Ensemble transform with rescaling	T126	21
Canada/CMC	15 days	Ensemble Kalman filter	TL213	21
Korea/KMA	10 days	Ensemble transform Kalman filter	N320	24
United Kingdom/UKMO	15 days	Ensemble transform Kalman filter	N214	24
Europe/ECMWF	10 days	Singular vectors	TL399	51

were defined as a period in which the daily temperature exceeds the threshold for more than two consecutive days.

The NCEP and National Center for Atmospheric Research (NCAR) reanalysis version 1 $2.5^\circ \times 2.5^\circ$ gridded daily data were used to characterize the large-scale atmospheric circulation field (Kalnay et al. 1996). The dataset includes daily maximum temperature, zonal and meridional wind at 200 hPa, geopotential height at 500 hPa, and sea level pressure. The sea surface temperature pattern associated with heat waves over South Korea was analyzed with the Optimum Interpolation Sea Surface Temperature (OISST) dataset provided by the Climate Diagnostics Center (CDC) of the National Oceanic and Atmospheric Administration (NOAA) (Reynolds et al. 2007). The daily outgoing longwave radiation (OLR) data were collected from the NCEP Climate Prediction Center (CPC) (Liebmann and Smith 1996).

The large-scale atmospheric circulations associated with heat waves for the June–August from 2011 to 2015 were examined with a composite analysis. The composite analysis defines the average fields on preidentified dates and has been used to examine large-scale atmospheric circulation patterns to provide physical insights (Grotjahn and Faure 2008).

b. Methodology of probabilistic prediction for heat waves over South Korea

According to Lee and Lee (2016), the occurrence of heat waves over South Korea is associated with large-scale atmospheric circulations such as the establishment of persistent high pressure and deep convection over the South China Sea. In particular, when deep convection occurs over the South China Sea, it becomes a source of the Rossby wave train pattern from the South China Sea to northeast Asia. It is a dominant mechanism associated with heat waves in South Korea from July to August. It is triggered by upward motion in the Northwest Pacific and downward motion in East Asia. The difference of vorticity at an upper level is related with the heat wave frequency in Korea at intra-seasonal time scales. Thus, they suggested the vertical motion can be applied to the forecast of heat waves over South Korea. Lee et al. (2016) proposed a HWI to predict the heat wave over South Korea and evaluated

the predictability of it based on the deterministic forecast using the TIGGE data. They reported that the proposed HWI has higher predictability of heat waves compared to maximum temperature for forecasting heat waves with the excessive threshold of 33°C over South Korea, particularly for 5–9-day forecast lead times. In this study, the HWI was defined as the vorticity difference at 200 hPa between the South China Sea and northeast Asia, that lie over $25^\circ\text{--}30^\circ\text{N}$, $110^\circ\text{--}130^\circ\text{E}$ and the average over $35^\circ\text{--}40^\circ\text{N}$, $120^\circ\text{--}140^\circ\text{E}$, respectively. A positive HWI value indicates a high probability of the heat wave over South Korea. Conversely, when HWI is negative, heat wave probabilities could be deemed low.

We developed and assessed the probabilistic forecast system of heat wave over South Korea using the HWI associated with large-scale circulations. The system was applied to predict HWI based on an ensemble prediction system from multiple climate predictions centers for the summer seasons from 2011 to 2015. It should be noted that the configuration of the ECMWF ensemble prediction system had been changed since 2016 (ECMWF 2019). Due to this change, the data from 2011 to 2015 were used for this study.

The occurrence probability of heat waves was estimated separately for each individual model as the fraction of ensemble members with HWI with above zero. These probabilities were then combined by a simple combination method with an equal weighting factor for the multimodel ensemble prediction.

c. Verification of probabilistic heat wave forecast

The verification metrics used to measure the forecast skill of individual model predictions and multimodel ensemble predictions include the Brier skill score (BSS), reliability diagram, and relative operating characteristics (ROC). These verification metrics are mainly event based, using the contingency table of “hit” H , “miss” M , “false alarms” F , and “correct rejections” R (Table 2).

The BSS is developed with Brier score (BS). The BS is commonly used to assess categorical probabilistic forecasts, which is analogous to the mean square error of a deterministic forecast (Wilks 2006). It is the mean square difference between forecasted and observed probabilities of an event occurrence. BS values close to

TABLE 2. The 2×2 contingency table.

Event forecast	Event observed		
	Yes	No	Marginal total
Yes	Hit (H)	False (F)	Yes forecasts ($H + F$)
No	Miss (M)	Correct negative (N)	No forecasts ($M + N$)
Marginal total	Yes obs ($H + M$)	No obs ($F + N$)	Total ($H + F + M + N$)

zero are preferred. A forecast skill score is generally defined as a proportion of the accuracy improvement over the accuracy of a reference forecast such as climatology or persistence. A positive value of BSS implies that the forecast is better than the climatology or reference forecasts. Therefore, BSS can be expressed as follows:

$$\text{BSS} = 1 - \frac{\text{BS}}{\text{BS}_{\text{ref}}}, \quad \text{BS} = \frac{1}{N} \sum_{i=1}^N (P_i - O_i)^2, \quad (1)$$

where N is the number of events, P_i is the probability forecast of event i , and O_i is equal to 1 or 0 depending on whether the event occurred or not, respectively.

We also calculated the ROC score from the categorical probability forecast in this study. The ROC verification is based on a traditional consideration for the hit rate H and false alarm rate F and measures the quality of a binary prediction based on the forecast probability. The ROC curve indicates the ability of the forecast to discriminate with observations in each category. ROC is plotted as a graph with the hit rates shown on the vertical axis and the false alarm rates shown on the horizontal axis. A useful summary measure of skill is the area under the ROC curve, which is 0.5 for a skill-less system and 1.0 for perfect forecasts.

The reliability diagram (Hsu and Murphy 1986) is widely used in verification of probabilistic forecasts for binary events such as the probability of measurable temperature and precipitation. This measures several attributes of probabilistic forecasts with respect to the observation: reliability, resolution, and sharpness. The reliability measures how close the forecast probabilities of an event are with respect to the observed frequency of the event, while the resolution measures how different the forecast probabilities are corresponding to the climatological probability of the event.

3. Results and discussion

First, we analyzed features of daily maximum temperature in summer seasons and the characteristics of large-scale circulation patterns associated with the top five heat waves during 2011–15. The top five heat waves were selected in terms of the magnitude defined as the sum of temperature surplus over 33°C during a heat

wave event. The selected heat wave events are summarized in Table 3 (and illustrated in Fig. 3 below with the hatched pattern). Figure 1 illustrates the intraseasonal variations for the daily maximum temperature over South Korea for June–August of 2011–15 relative to the 1981–2010 climatological periods. Time series of daily maximum temperature based on the 60 stations over South Korea indicated as positive (red) and negative (blue) temperature anomalies relative to the period of 1981–2010.

It was shown that daily maximum temperatures in the summer season of 2011 largely fluctuated (Fig. 1a). As shown Fig. 1a, the heat wave that occurred from 2 to 7 August 2011 was selected the fifth major heat wave event during 2011–15. Figure 1b illustrates the time series of daily maximum temperature in 2012. It shows a severe heat wave affected Korea during summer in 2012, with sustained amplitudes of the daily maximum temperature anomaly approximately 3°C above the 1981–2010 climatological average. In particular, from 22 July to 12 August, daily maximum temperatures remained above 30°C across the country and the first heat wave warning was issued since the heat wave alarm system was adopted in 2008. These periods (starting on 19 July and ending on 12 August 2012) were selected as the second major heat wave event over South Korea during the study periods. The heat wave, resulting in 14 death and 975 heat-related illnesses over the country, lasted for 25 days (Na et al. 2013). In summer 2013, the daily maximum temperature recorded were approximately 30°C , which was the second hottest summer since 1954 (Fig. 1c). It was 1.6°C above the normal (i.e., 28.3°C) for the period of 1981–2010. The minimum temperature of 21.7°C and the mean temperature of 25.4°C in the summer of 2013 were the highest in South Korea over the recent 30 years. In particular, a persistent heat wave (starting on 6 July and

TABLE 3. The top five heat wave events in the period 2011–15.

Case	Date	Duration (days)
1	30 Jul–23 Aug 2013	25
2	19 Jul–12 Aug 2012	25
3	25 Jul–10 Aug 2015	17
4	9–28 Jul 2013	20
5	2–7 Aug 2011	6

FIG. 1. (a)–(e) Time series of the anomalies of the daily maximum temperatures averaged over the 60 stations for the summers 2011–15 relative to the 1981–2010 climatological average, illustrating the top five events of heat waves (hatched). Case 1: 30 Jul–23 Aug 2013, case 2: 19 Jul–12 Aug 2012, case 3: 25 Jul–10 Aug 2015, case 4: 9–28 Jul 2013, and case 5: 2–7 Aug 2011.

ending on 23 August 2013) was sustained with very large positive anomalies compared to a reference value.

The five events selected in this study (Table 3) were used for the composite analysis. The meteorological anomaly fields for composites of 200-hPa vorticity, outgoing longwave radiation, 500-hPa geopotential height, and sea level pressure for heat wave events are shown in Fig. 2. A significant anomalous anticyclone is observed with its center over the Korean peninsula as observed (Fig. 2a). Associated with these positive geopotential anomalies over northeast Asia, the descending motion can reduce precipitation and total cloud cover and thus increase downward solar radiation. Moreover, the dipole pattern between the South China Sea and northeast Asia was dominant (Fig. 2b), providing a consistent implication with Lee and Lee (2016) and

Lee et al. (2016). The OLR anomalies as a proxy for anomalous large-scale convective activity showed that there was a negative OLR anomaly, which is convective activity, over the South China Sea in the heat wave events (Fig. 2d). In turn, deep convection in the South China Sea becomes a source of the Rossby wave train pattern from the South China Sea to northeast Asia, causing descending motion as shown Fig. 2a and favoring the large-scale circulation triggering extreme conditions over South Korea. This suggests that the enhancement of North Pacific high and convection activities over the South China Sea are important factors leading to the heat wave over South Korea (Lee and Lee 2016; Xu et al. 2019).

We explored the forecast of significant heat waves that occurred across South Korea in July–August 2013

FIG. 2. Composite maps of (a) 500-hPa geopotential height anomaly (shading; 5-gpm interval), (b) 200-hPa vorticity anomaly (shading; $0.4 \times 10^{-6} \text{ s}^{-1}$ interval), (c) sea level pressure (shading; 0.4-hPa interval), and (d) outgoing longwave radiation (shading; 4 W m^{-2} interval) for the top five heat wave events in the period of 2011–15. The dots indicate statistical significance exceeding the 95% confidence level based on a Student's *t* test. The box in (b) indicates the regions used to calculate the HWI.

using the HWI associated with the large-scale circulation. Figure 3 shows the occurrence probability of heat waves over South Korea for each model separately, as well as a multimodel ensemble. The horizontal axis shows forecast lead time, and the vertical axis shows the initial date of forecast. Figure 3a shows the occurrences of heat wave event over South Korea which are observed in the summer of 2013. For a forecast lead time of 1–4 days, the observed heat waves from July to August 2013 were well predicted by the all models, generally with a high probability above 0.8. However, they failed to acceptably capture the observed heat wave in June 2013, particularly for the onset. This drawback can be explained by the definition of the HWI in this study. The HWI was defined as difference based on the dipole pattern in the 200-hPa vorticity, which is associated with large-scale circulation leading to heat waves in South Korea for July and August. Furthermore the characteristic features of the South Korea surface air temperature during the early (June) and the late summer (July–August) in association with atmospheric and oceanic circulations are quite different. The South Korea surface air temperature in June is associated with land–sea thermal contrast around East Asia. On the other hand, the

enhanced convective activity over western tropical Pacific is an important factor that affects the South Korea surface air temperature in July and August (Yeo et al. 2017).

Each model well predicted the heat waves in July and August 2013 with a high-occurrence probability of heat waves for 1–5 days of forecast lead. At longer forecast lead times, UKMO, ECMWF, and the multimodel ensemble showed higher occurrence probabilities of heat waves than those of other centers, while the occurrence probabilities from CMC and NCEP were rapidly dropped. For example, CMC and NCEP predicted approximately 30% probability of occurrence of heat wave on 21 July at 7-day forecast lead time. On the other hand, the occurrence probability of heat wave from UKMO and ECMWF remained about 70% at 10-day forecast lead time.

The probabilistic forecasts of HWI were verified using the BSS to quantify the medium-range forecast skill. Figure 4 shows the results of BSS for the occurrence of heat wave events by NCEP, CMC, KMA, UKMO, ECMWF, and the multimodel ensemble-based probabilistic forecasts with forecast lead times. The NCEP model performance was lowest for the entire range of forecast lead times. The BSS values of NCEP compared with other ensemble system notably decreased at forecast

FIG. 3. (a) The occurrence of the observed heat waves, and the probability of the occurrence of heat waves for each model (b) NCEP, (c) CMC, (d) KMA, (e) UKMO, (f) ECMWF, and (g) the multimodel ensemble in June–August 2013.

lead times of 5–11 days. On the other hand, the multimodel ensemble performed better than other ensemble systems for all forecast lead times. The BSS values of the multimodel ensemble were higher than 0.70 up to a forecast lead time of 14 days. These results are in good agreement with those of Matsueda and Nakszawa (2015). They reported that the multimodel ensemble provided more reliable forecasts than single NWP center ensembles for the severe weather event. The multimodel ensemble improved the predicting skill of heat waves for a longer forecast time of 5 days. These results led us to believe that a multimodel ensemble system for the heat wave forecasts should be more favored than the use of any single model ensemble system. This is partly supported by higher skill scores from the results of Weigel et al. (2008).

Figure 5 illustrates the ROC curves relative to the probabilistic forecast and the difference of ROC scores between 5 and 9 days of forecast lead time. The area under the curves in the plot of hit rates versus false alarm rates defined as the ROC score is a useful summary measure of a forecast skill. As shown Fig. 5, all the ROC curves were very far from the diagonal line. This diagonal line represents no skill of forecast. The differences

between the areas of the single NWP center and the multimodel ensemble were not very large at 5 days of forecast lead time. However, the ROC score of the multimodel ensemble stays still higher than any of the single model predictions. Even though the areas have a tendency to decrease as forecast lead times increased, a change in the area was smallest in the multimodel ensemble system except for KMA. These results indicate the superiority of multimodel ensemble for HWI forecasts.

We also presented the reliability diagram for the probability of heat wave occurrence in Fig. 6. The diagonal line (a solid line) represents perfect reliability on which the forecast probability equals the observed frequency. As can be seen, the curves for a single NWP center and the multimodel ensemble were quite close to the perfect reliability line. But the resolution of a reliability diagram should be treated with caution because of the small sample sizes for heat wave occurrences in this study.

4. Summary and conclusions

This study attempted to apply large-scale patterns to predict heat waves and to assess probabilistic forecasts

FIG. 4. The BSS of probabilistic forecast of the occurrence of heat waves, for each model (NCEP, CMC, KMA, UKMO, and ECMWF) and the multimodel ensemble with forecast lead times.

based on a multimodel ensemble forecast system for heat waves over South Korea for the summers of the years 2011–15. The large-scale atmospheric circulations of the top five heat wave events over South Korea for the period of 2011–15 presented a significant anomalous

anticyclone with their centers appearing over the Korea peninsula and the dipole pattern between the South China Sea and northeast Asia. Deep convection in the South China Sea becomes a source of the Rossby wave train pattern from the South China Sea to northeast

FIG. 5. ROC curves of probabilistic forecast of the occurrence of heat waves for forecast lead times of (a) 5, (b) 6, (c) 7, (d) 8, and (e) 9 days; (f) the difference of ROC score between forecast lead times of 5 and 9 days. The numbers in parentheses represent the area under the curve.

FIG. 6. Reliability diagram of probabilistic forecast of the occurrence of heat waves for forecast lead times of (a) 5, (b) 6, and (c) 7 days.

Asia. These results are in good agreement with those of Lee and Lee (2016) and Xu et al. (2019). They reported that enhancement of North Pacific high and convection activity over the South China Sea may lead to heat waves over South Korea. The dipole pattern of the 200-hPa vorticity between the South China Sea and northeast Asia can be applied as a predictant for heat waves over South Korea.

The single model ensemble systems from TIGGE and the multimodel ensemble were assessed to predict heat waves over South Korea. It is notable that a high-occurrence probability of heat waves with the UKMO, ECMWF, and multimodel ensemble forecast lasted at longer forecast lead times, while that with CMC rapidly dropped as the lead time increased. This study revealed that the multimodel ensemble system could reasonably predict the onset and duration of the heat waves over South Korea with a sufficient lead time to prepare for imminent heat wave in advance.

In addition, it was found that the ROC scores of the multimodel ensemble stay higher than those of single NWP centers with forecast lead time. The results indicate that the multimodel ensemble is capable of better predicting the large-scale circulation patterns leading to heat waves over South Korea than other single ensemble systems through all forecast lead times. We conclude that the probabilistic forecast of heat waves can be useful to take appropriate and timely actions to minimize the loss of lives and properties.

It should be noted that local features such as geographic locations, land cover, and local soil moisture, play important roles can trigger and persist extreme heat events (Yang et al. 2018). However, the local features are not considered in this study. A further study on these local features is recommended.

Acknowledgments. This research was supported by the APEC Climate Center.

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