The Dependence of Daily and Hourly Precipitation Extremes on Temperature and Atmospheric Humidity over China

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ABSTRACT

Precipitation extremes are expected to increase by 7% per degree of warming according to the Clausius–Clapeyron (CC) relation. However, this scaling behavior is inappropriate for high temperatures and short-duration precipitation extremes. Here, daily data from 702 stations during 1951–2014 and hourly data from 8 stations during 2000–15 are used to examine and explain this behavior in China. Both daily and hourly precipitation extremes exhibit an increase in temperature dependency at lower temperatures. The CC scaling transitions from positive to negative rates with temperatures greater than 25°C. Unlike the increase in daily data, which is similar to single-CC (1CC) scaling, the increase in hourly data resembles super-CC (2CC) scaling for temperatures greater than 13°C. Results show that the precipitation extremes are controlled by water vapor for a given temperature. At lower temperatures, precipitation extremes exhibit a positive linear dependence on daily actual vapor pressure whose value is almost equal to the saturated vapor pressure at a given temperature. At higher temperatures, actual vapor pressure has difficulty maintaining a consistent increasing rate because of the exponential increasing of the saturated vapor pressure. Higher temperatures result in larger vapor pressure deficits, which lead to sharp decreases in precipitation extremes. Similar scaling behaviors are obtained in 10 river basins over China, where the breaking point temperature increases from 17°C along the northwest inland area to 25°C along the southeast coast. These behaviors demonstrate that precipitation extremes are firmly linked to temperature when there is sufficient moisture at lower temperatures and limited by insufficient moisture at higher temperatures. Overall, precipitation extreme events require more attention in a warming climate.

1. Introduction

Evidence that precipitation extremes are increasing globally has strengthened considerably in recent years (Berg et al. 2013; Fischer and Knutti 2016;

Lenderink and Meijgaard 2008; Westra et al. 2014). Precipitation extremes are expected to increase by 7% per degree of warming according to the Clausius–Clapeyron (CC) relation, which states that the atmosphere can hold approximately 6%–7% more water vapor per degree of warming before saturation occurs (Lenderink and Meijgaard 2008; Trenberth et al. 2003). However, this scaling behavior does not appear to be appropriate for high temperatures (Busuioc et al. 2017; Chan et al. 2016; Drobinski et al. 2016; Wang et al. 2017) and short-duration precipitation extremes

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(Haerter and Berg 2009; Jones et al. 2010; Lenderink and Meijgaard 2008).

Negative scaling behaviors because of high temperatures for both daily and subdaily precipitation extremes have been found in the Amazon and Congo basins, the tropical Pacific, the Indian monsoon region, the U.S. Midwest, central Europe (Wang et al. 2017), Romania (Busuioc et al. 2017), the United Kingdom (Chan et al. 2016), the Mediterranean (Drobinski et al. 2016), Australia (Jones et al. 2010), Japan (Utsumi et al. 2011), South Korea (Park and Min 2017), and China (Huang et al. 2017; Sun et al. 2013; Xiao et al. 2016). Additionally, the breaking point temperature (the temperature for the CC scaling transition from positive to negative rates) has been found to be different in different study areas, and it is $\sim 22^{\circ}\text{C}$ in the United Kingdom (Chan et al. 2016), 20°C in the Mediterranean (Drobinski et al. 2016), 26°C in Australia (Jones et al. 2010), $\sim 20^{\circ}\text{--}24^{\circ}\text{C}$ in southeastern Austria (Schroeder and Kirchengast 2018), 25°C in China (Huang et al. 2017; Sun et al. 2013; Xiao et al. 2016), and 18°C during spring and summer at the 99.9th percentile in Romania (Busuioc et al. 2017). Short-duration precipitation extremes have exceeded CC relation expectations, and a transitional behavior from single-CC (1CC) to super-CC (2CC) scaling for hourly precipitation extremes has been found (Haerter and Berg 2009; Lenderink and Meijgaard 2008). Station observations suggested that 1-h precipitation extremes increase twice as fast with rising temperatures, as expected from the 1CC relation, when daily mean temperatures exceed 12°C (Haerter and Berg 2009; Lenderink and Meijgaard 2008).

Model predictions have shown that future daily precipitation extremes will continue to intensify (Donat et al. 2016), and the observed scaling rates of precipitation extremes are found to be larger than that predicted by models, implying that future changes in precipitation extremes may still be underestimated (Allan and Soden 2008) because of the change in water vapor (Bao et al. 2017). Barbero et al. (2017) have suggested that it may be helpful to determine whether or not future changes in precipitation extremes are likely to exceed observed scaling rates that are estimated using dewpoint temperature variations rather than surface temperature. Future hourly precipitation extremes cannot simply be extrapolated from daily precipitation extremes scaling analyses, and the models cannot provide a reliable extrapolation basis until improved methods are available (Chan et al. 2016; Zhang et al. 2017).

Atmospheric humidity, precipitation type and duration, microphysics, El Niño events, orography, anthropogenic aerosols, and greenhouse gases have been thought to influence the scaling behaviors of precipitation extremes at higher temperatures or for short durations. First, atmospheric moisture availability with increasing temperatures

has been identified as a particularly large influence on scaling. The increase in daily precipitation intensity has also been strongly associated with the increase in water vapor (Ye et al. 2015). Both observations and models show a strong reduction in relative humidity at higher temperatures, which reflects how moisture availability becomes the dominant driver in extreme precipitation events (Jones et al. 2010; Sun et al. 2015; Xiao et al. 2016). Several results have shown that the dewpoint temperature has been used as an alternative measure with which to investigate the combined effect of atmospheric temperature and moisture availability that drives precipitation extremes (Barbero et al. 2017; Westra et al. 2014). Trenberth et al. (2003) have argued that because heavy rainfall rates greatly exceed evaporation rates and thus depend on low-level moisture convergence, the rainfall intensity should also increase at about the same rate as the moisture increases, namely, $7\% \text{ K}^{-1}$ with warming. In fact, the rate of increase can even exceed this because the additional latent heat released feeds back and invigorates the storm that causes the rain in the first place, further enhancing convergence of moisture (Trenberth et al. 2003; Liu et al. 2009). Therefore, precipitation extremes increase with temperature in moist, energy-limited environments and decrease abruptly in dry, moisture-limited environments (Prein et al. 2017). Second, precipitation can be separated into convective and stratiform events based on cloud observations (Berg et al. 2013) or the presence of lightning (Molnar et al. 2015). Convective precipitation has a more sensitive response to temperature increases than that from stratiform precipitation, which has increasingly dominated subdaily precipitation extremes (Berg et al. 2013; Busuioc et al. 2017; Molnar et al. 2015; Singleton and Toumi 2013) because of the increased propagation of squall lines (Singleton and Toumi 2013); these events exhibit typical convective precipitation structures, which scaling breaks down at higher temperatures (Singleton and Toumi 2013). And results of models and simulations also imply that the convective systems drive precipitation extremes (Meredith et al. 2015; Moseley et al. 2016). Other results have shown that CC scaling is also mainly dependent on precipitation duration (Utsumi et al. 2011; Sun et al. 2013), cloud and precipitation microphysics (Singh and O’Gorman 2014), El Niño events (Allen and Luptowitz 2017), orography (Drobinski et al. 2016), and anthropogenic aerosols and greenhouse gases (Chen et al. 2011; Min et al. 2011).

Intense precipitation extreme events create complex processes and involve multiple factors, which makes it challenging to examine and explain their behaviors, especially for China. Research in this area is quite poor and China includes many climatic regions, which makes the problem even more complicated. Here, we used

FIG. 1. The locations of meteorological stations. (a) Daily meteorological stations and 10 river basins over China. (b) Hourly meteorological stations, including ASA, CWA, LCA, YGA, NMD, SPD, GGF, and QIA.

TABLE 1. The information of the daily database and its precipitation events.

Database		Data of precipitation events			
Mean temperature	>25°C	<0°C	Proportion	Mean temperature	>25°C
11.58°C	13.64%	17.60%	29.28%	15.47°C	14.15%

temperature, precipitation, and water-vapor-related variables [actual vapor pressure e_a , specific humidity q , relative humidity (Rh), and pan evaporation E_{pan}] to study the dependence of daily and hourly precipitation extremes on temperature and atmospheric humidity over China. In section 2, we describe the data and methods. Section 3 reports the results of the relationship between temperature and precipitation extremes and attempts to explain the results quantitatively, which is then followed by the conclusion. The abbreviation of variables in the manuscript is shown in the appendix.

2. Data and methods

Figure 1 shows the spatial locations of the meteorological stations. Figure 1a shows the daily data stations and 10 river basins in China. Figure 1b shows the hourly data stations. The daily surface data during 1951–2014 are obtained from 702 meteorological stations associated with the China Meteorological Data Service Center (CMDC; <http://data.cma.cn>; Fig. 1a). The data have been strictly quality controlled (CMDC 2012) and contain approximately 6325 552 data points. Daily precipitation amounts larger than 0.1 mm day^{-1} are defined as precipitation events. The information of the daily database and its precipitation events is shown in Table 1. The E_{pan} is observed by a D20 pan (i.e., an evaporative pan), which has a 20-cm diameter and 10-cm-high walls.

Hourly surface data from 2000 to 2015 are obtained by eight field experiments and monitoring stations (Fig. 1b), including Ansai (ASA), Changwu (CWA), Luancheng (LCA), Yanting (YGA), Naiman (NMD), Shapotou (SPD), Gongga Shan (GGF), and Qiyang (QIA), China, which are provided by the Chinese Ecosystem Research Network (CERN; <http://www.cern.org.cn>) and support ecological, climatic, and agricultural-related research (Wang et al. 2016; Lu et al. 2016; Zhang et al. 2016). The data are measured hourly with the Milos 520 data collection and processing system, which is an automatic weather station produced by the Vaisala Company (Finland) and has field-proven reliability and accuracy (<http://www.vaisala.com/en/Pages/default.aspx>). The data have been strictly quality controlled and contain approximately 592 841 data points, of which 6.38% have intensities greater than 0.1 mm h^{-1} .

Here, we reproduce the CC scaling method using the Lenderink and Meijgaard (2008) methodology. Daily precipitation intensity I_d is binned using daily mean

temperature at 2-m height T , and hourly precipitation intensity I_h and q are binned using T_d or the hourly mean temperature at 2-m T_h , where the width of each bin is 2°C . Wet events are defined by hours with precipitation values $> 0.1 \text{ mm h}^{-1}$. The 90th confidence intervals are estimated by the bootstrap method. The 99.9th, 99th, 95th, 90th, and 75th percentiles computed from the raw data falling within the confidence interval are estimated from the bootstrap method, where the bootstrap results are based on 1000 bootstrap samples using the International Business Machines Corporation (IBM) Statistical Product and Service Solutions (SPSS) Statistics, version 22.0. The hourly q is calculated from the hourly e_a and atmospheric pressure at each station (Ye et al. 2015).

3. Results and discussion

a. The dependence of daily precipitation extremes on temperature and atmospheric humidity

1) THE RELATIONSHIP BETWEEN DAILY PRECIPITATION EXTREMES AND TEMPERATURE

Figure 2 shows the 99.9th, 99th, 95th, 90th, and 75th percentiles of daily precipitation intensity I_d compared with the CC relation. Different percentiles of I_d exhibit

FIG. 2. Daily precipitation intensity I_d dependence on T . Solid color lines represent the 99.9th, 99th, 95th, 90th, and 75th percentiles. Gray bands represent the 90th percentile confidence intervals estimated by the bootstrap method. Dotted lines represent the 1CC (black) and 2CC (red) relations.

FIG. 3. (a)–(j) Daily precipitation intensity dependence on temperature over 10 river basins in China. (k) The breaking point temperatures of the 10 river basins. Solid color lines represent the 99.9th, 99th, 95th, 90th, and 75th percentiles. Gray bands represent the 90th percentile confidence intervals estimated by the bootstrap method. Dotted lines represent the 1CC (black) and 2CC (red) relations.

similar scaling behaviors. For T roughly below 25°C , the different percentiles of I_d exhibit a temperature dependency similar to that of the 1CC relation. While T is larger than 25°C , I_d sharply decreases with an increase in temperature. This positive–negative scaling behavior is consistent with results found in the Amazon and Congo

basins, the tropical Pacific, the Indian monsoon region, the U.S. Midwest, central Europe (Wang et al. 2017), Romania (Busuioc et al. 2017), the United Kingdom (Chan et al. 2016), the Mediterranean (Drobinski et al. 2016), Australia (Jones et al. 2010), Japan (Utsumi et al. 2011), and South China (Sun et al. 2013).

China includes many climatic regions, and the 10 river basins in this study divide and represent these different climate zones. To examine if this scaling behavior is the same in different regions, we analyze the relationships between different percentiles of I_d and T , which results in similar scaling behaviors among different regions (Fig. 3). When T is lower than the breaking point temperature, I_d exhibits a positive 1CC relation dependence on temperature. Figures 3h–j exhibit a weaker 1CC scaling behavior. Figures 3h–j contain rivers in the southeast, southwest, and northwest, so each of them has multiple basins, while the other panels contain only one basin (e.g., the rivers of Fig. 3a belong to the Chang River basin). It may be because multiple basins cause unstable relationships between I_d and T . Figure 3j, which encompasses the northwest region that crosses the Qinghai–Tibetan Plateau, shows a transition from a 1CC scaling to a lower-rated scaling for higher temperature. Schroeer and Kirchengast (2018) also found that temperature sensitivities in the mountainous western region of China were weaker than those in the eastern lowlands of southeastern Austria; this was most likely because moisture was not locally sourced, which led to weaker temperature sensitivities (Schroeer and Kirchengast 2018; Zhang et al. 2017). Each basin has a distinct breaking point, where the breaking point temperature ranges from 17°C to 25°C (Fig. 3k), which is consistent with values found in other study areas [e.g., 22°C in the United Kingdom (Chan et al. 2016), 20°C in the Mediterranean (Drobinski et al. 2016), 26°C in Australia (Jones et al. 2010), 25°C in South China (Sun et al. 2013), and 18°C in Romania (Busuioc et al. 2017)]. More importantly, the breaking point temperature gradually increases from the northwest inland area to the southeast coast, which is consistent with increasing patterns of precipitation, cloud amount, total cloud cover, and Rh across China. This pattern suggests that the breaking point temperature depends on water vapor availability for the occurrence of precipitation and on the distance from the basin to the coast.

2) THE RELATIONSHIP BETWEEN ATMOSPHERIC HUMIDITY AND TEMPERATURE

Actual vapor pressure is the partial pressure of water vapor at a given temperature. Relative humidity measures how much water the air currently contains as compared to what it would contain if saturated. Evaporation reflects part of the vertical transport of water vapor. All of these are different ways of measuring the amount of water vapor in the atmosphere. We use the abovementioned method to analyze the relationships among e_a , Rh, E_{pan} , and T under the 99.9th, 99th, 95th, 90th, and 75th,

FIG. 4. Temperature relationships with daily precipitation, humidity, and evaporation: (a) e_a , (b) Rh, and (c) E_{pan} . Solid color lines represent the 99.9th, 99th, 95th, 90th, and 75th percentiles. Gray bands represent the 90th confidence intervals estimated by the bootstrap method. Dotted lines represent the 0.5CC (gray), 1CC (black), and 2CC (red) relations. The dash-dot line represents the breaking point temperature.

90th, and 75th percentiles. Figure 4a shows different e_a percentiles compared with the CC relation. For lower temperatures, e_a is strictly controlled by the CC curve and increases at an approximate rate of 7% per degree of warming. When T increases to approximately 25°C, a breaking point occurs. When T continually increases, the temperature dependency of e_a transitions from a 1CC relation to a 0.5CC (or smaller) relation.

Figure 4b shows changes of Rh for different percentiles. Relative humidity begins to increase as T increases,

FIG. 5. Percentiles for E_{pan} vs vapor pressure deficit. The vapor pressure deficit is the difference between e_s and e_a . Scatterplots represent the 99.9th, 99th, 95th, 90th, and 75th percentiles. Solid lines and equations explain the trend lines and fitted formulas of the scatterplots.

then gradually stabilizes at high levels, and sharply decreases when T is greater than 25°C. Both observations and previous model results have shown similar reductions in Rh at high temperatures (Jones et al. 2010; Sun et al. 2015; Xiao et al. 2016). This scaling behavior is consistent with that of e_a because saturated vapor pressure e_s increases exponentially with temperature.

Figure 4c shows changes of E_{pan} for different percentiles. Pan evaporation linearly increases with temperature at lower temperatures, and when T is greater than 25°C, the rate of E_{pan} rapidly increases. The different percentiles of E_{pan} show the same trend with T increasing. They are positively correlated with vapor pressure deficits (i.e., the difference between e_s and e_a ; Fig. 5), which are consistent with previous research results and related E_{pan} calculations or models, such as Dalton's (Dalton 1802) and Penman's (Allan et al. 1998) equations of evaporation from water surface.

The relationships among daily I_d , Rh, e_a , E_{pan} , and T under the 99.9th, 99th, 95th, 90th, and 75th percentiles are analyzed in the 10 basins. Figure 6 shows the result of the 99.9th percentile, which indicates that the corresponding breaking point temperatures for I_d , Rh, e_a , and E_{pan} are identical in the same basin. When T is lower than the breaking point temperature and as T increases precipitation extremes increase, e_a increases strictly along the CC curve, Rh is almost stable at 100%, and the increasing rate of E_{pan} stabilizes. When T is greater than the breaking point temperature, I_d and Rh decrease rapidly, the increasing rate of e_a slows down, and the E_{pan} rate begins to accelerate. The 99th, 95th,

90th, and 75th percentiles for the 10 basins are shown in Figs. S1–S4 in the online supplemental material.

3) THE RELATIONSHIP BETWEEN DAILY PRECIPITATION EXTREMES AND WATER VAPOR

To show the direct relationship between I_d extremes and water vapor, I_d is binned using daily e_a . The width of each bin is 2 hPa. The e_a effect at the 99.9th, 99th, 95th, 90th, and 75th percentiles on I_d is shown in Fig. 7a (solid color lines). The different percentiles of I_d exhibit a positive–negative e_a dependency similar to that of the $I_d \sim T$ relation (Fig. 2). When e_a is lower than the breaking point, I_d exhibits a positive linear dependence on e_a , and the correlation coefficient is not less than 0.98 (Fig. 7b).

Because e_s is the maximum partial pressure of water vapor in the air and varies with the temperature of the air and water vapor mixture, T and e_a are connected by e_s for studying precipitation extremes. Daily precipitation intensity is binned using daily e_s , and the width of each bin is 2 hPa. The relationship of I_d and daily e_s at different percentiles is shown in Fig. 7a (dash-dot-dot color lines). The two lines are very similar and have the same trend, and e_a is slightly smaller than e_s for a given I_d under the same percentiles.

The medium gray dashed line in Fig. 7a is the e_s value at a given temperature based on the Goff–Gratch equation (Goff and Gratch 1946; Goff 1957), which described how to calculate the e_s above a flat, free-water surface as a function of temperature and was recommended for use by the World Meteorological

FIG. 6. (a)–(j) The 99.9th percentile for I_d , e_a , Rh, and E_{pan} in 10 river basins. (k) The breaking point temperatures for the 10 river basins. Gray bands represent the 90th percentile confidence intervals estimated by the bootstrap method. Dotted lines represent the 0.5CC (gray), 1CC (black), and 2CC (red) relations. The dash-dot line represents the breaking point temperature.

Organization in 1988, with further corrections in 2000. Figure 7a shows that the breaking points for e_a and e_s are 29.03 and 30.93 hPa, and its corresponding breaking point temperature is 24.6°C, which is close to 25°C of the $I_d \sim T$ relation (Fig. 2).

Overall, because precipitation extremes tend to occur when the atmosphere is close to saturation at lower temperatures, precipitation extremes increase with warming in proportion to the increase in surface

moisture storage capacity, which exponentially increases at a 1CC scaling rate as temperature increases (Singh and O’Gorman 2014; Wang et al. 2017). In this situation, precipitation extremes respond to temperature changes in the absence of moisture limitation. When the temperature is higher than the breaking point temperature (i.e., higher temperature), e_a has difficulty maintaining a consistent increasing rate as e_s increases exponentially, so higher temperatures result in larger

FIG. 7. Daily precipitation intensity I_d dependence on e_a . (a) Different percentiles of I_d vs e_a (solid color lines) and e_s (dash-dot-dot color lines). The medium gray dash line is the e_s value at a given T . Gray bands represent the 90th percentile confidence intervals estimated by the bootstrap method. (b) Different percentiles of I_d vs e_a when e_a is lower than the breaking point. The color equations explain the trend lines and fitted formulas of the corresponding color scatterplots.

vapor pressure deficits, which leads to a sharp increase in precipitation extremes. And similar scaling behaviors are obtained in 10 river basins over China, where the breaking point temperature depends on the distance from the coast to the basin and increases from 17°C along the northwest inland area to 25°C along the southeast coast. This pattern suggests that insufficient moisture availability inhibits the development of precipitation extremes.

b. The dependence of hourly precipitation extremes on temperature and atmospheric humidity

1) THE RELATIONSHIP BETWEEN HOURLY PRECIPITATION EXTREMES AND TEMPERATURE

Figure 8 shows the 99.9th, 99th, 95th, 90th, and 75th percentiles for hourly precipitation intensity I_h under T , daily maximum air temperature T_{dmax} , minimum air temperature T_{dmin} temperature at 2-m height in a day, and T_h . The scaling behaviors among I_h and T (Fig. 8a), T_{dmax} (Fig. 8c), T_{dmin} (Fig. 8d), and T_h (Fig. 8b) are generally similar. Hourly precipitation intensity increases at lower temperatures, then fluctuates from positive to negative under temperatures exceeding the breaking point temperature, indicating scaling similar to that for daily temperatures. The corresponding breaking point temperatures are approximately 23°–25°C for T , T_{dmin} , and T_h , but temperatures are higher for T_{dmax} . However, the increasing rates of I_d and I_h are different when the temperature is lower than the breaking point temperature. Daily precipitation intensity exhibits a temperature dependency similar to the 1CC rate. Hourly precipitation intensity exhibits an increasing rate similar to the 1CC relation at lower temperatures, which

increases to a 2CC relation at higher temperatures. This scaling behavior is more distinct for higher percentiles (i.e., 99.9th and 99th) and weaker for lower percentiles (75th and 90th). The corresponding T transitions from 1CC to 2CC are approximately 13°C for the 99.9th and 99th percentiles and 17°C for the 95th percentile. The corresponding T_h transitions are approximately 11°C for the 99.9th and 99th percentiles and 13°C for the 95th percentile. This transition behavior for I_h from a 1CC to 2CC scaling (when T exceeds approximately 12°C) has been identified (Haerter and Berg 2009; Lenderink and Meijgaard 2008). And some results imply that the convective field or systems drive this scaling based on cloud observations (Berg et al. 2013), the presence of lightning (Molnar et al. 2015), or simulations (Meredith et al. 2015; Moseley et al. 2016). Because the atmospheric temperature at 2 m is different from the temperature at the height of clouds, this difference in temperature may also affect extreme precipitation analysis. Atmospheric humidity (Trenberth et al. 2003; Liu et al. 2009), precipitation type (Berg et al. 2013) and duration (Utsumi et al. 2011; Sun et al. 2013), cloud and precipitation microphysics (Singh and O’Gorman 2014), El Niño events (Allen and Luptowitz 2017), orography (Drobinski et al. 2016), and anthropogenic aerosols and greenhouse gases (Chen et al. 2011; Min et al. 2011) have been thought to influence the scaling behaviors of precipitation extremes at higher temperatures or for short durations.

2) THE RELATIONSHIP BETWEEN HOURLY ATMOSPHERIC HUMIDITY AND TEMPERATURE

Figure 9 shows the relationship of temperature to e_a , Rh, and q under the 99.9th, 99th, 95th, 90th, and 75th

FIG. 8. Hourly precipitation intensity dependence on temperature. (a) Observed 1-h precipitation intensity vs T , (b) T_h , (c) T_{dmax} , and (d) T_{dmin} . Solid color lines represent the 99.9th, 99th, 95th, 90th, and 75th percentiles. Gray bands represent the 90th percentile confidence intervals estimated by the bootstrap method. Dotted lines represent the 1CC (black) and 2CC (red) relations.

percentiles. Figures 9a–c and Figs. 9d–f show the results for T and T_h , respectively. The scaling behaviors of each variable are similar for T and T_h , while the fluctuation in T_h scaling is stronger because T_h is mainly controlled by boundary layer processes and radiation (Lenderink and Meijgaard 2008). When the temperature is lower than the breaking point temperature, e_a exhibits a temperature dependency similar to the 1CC rate. Rh begins to increase as T increases, then gradually stabilizes. The q exponentially increases first, then transits toward a linear increase. Overall transition temperatures (13°C for the 99.9th and 99th daily percentiles and 17°C for the 95th percentile) are in agreement with those of T_h , which are approximately 11°C for the 99.9th and 99th percentiles and 13°C for the 95th percentile. This scaling behavior is weaker for lower percentiles, where the

transition temperature is higher. The breaking point temperature is approximately 25°C for T and 23°C for T_h . When the temperature is greater than the breaking point temperature, e_a and q slightly increase or maintain stability, and Rh decreases sharply with an increase in temperature.

Hourly intensity is binned using hourly q data, and the width of each bin is 2 g kg^{-1} . The q and T effect at the 99.9th, 99th, 95th, 90th, and 75th percentiles on I_h are compared in Fig. 10. The two lines under the same percentile are very similar and have the same trend.

Both daily and hourly results showed that temperature changes in water vapor–related variables, precipitation, e_a , q , Rh, and E_{pan} are similar, especially the breaking points. These variables also have a very strong basis for observations. When the temperature is lower, e_a is strictly controlled by the CC curve;

FIG. 9. Relationships among temperature, hourly precipitation, and humidity for (left) T and (right) T_h , with (a),(d) e_a , (b),(e) Rh, and (c),(f) q . Solid color lines represent the 99.9th, 99th, 95th, 90th, and 75th percentiles. Gray bands represent the 90th percentile confidence intervals estimated by the bootstrap method. Dotted lines represent the 0.5CC (gray), 1CC (black), and 2CC (red) relations. The dash-dot line (black) represents the breaking point temperature, and the dash-dot line (gray) represents temperature that increases the rates of 99.9th and 99th percentile precipitation values that transitioned from 1CC to 2CC.

Rh increases first, then stabilizes; precipitation extremes increase continuously and exhibit a positive dependence on e_a or q . In this situation, e_a is approximately equal to e_s , and precipitation extremes result from temperatures with sufficient moisture capacity. However, for higher temperatures, e_a slightly decreases or remains stable and Rh sharply decreases, which leads to larger vapor pressure deficits, and precipitation extremes sharply decrease. In this situation, precipitation extremes result from high temperatures with insufficient moisture capacity. Both daily and hourly precipitation extremes result from humidity control at the same temperature. It should be pointed out that sufficient moisture capacity and insufficient moisture capacity are both at an atmospheric temperature of

2 m, which is different from the temperature at the height of clouds.

4. Conclusions

Precipitation extreme events become more intense in a warmer climate. Based on data for 16 325 552 days at 702 meteorological stations over China during 1951–2014, we find that when the temperature is lower than 25°C, precipitation extremes exhibit a temperature dependency similar to the 1CC relation, which decreases sharply with temperatures greater than 25°C. A similar scaling behavior is obtained in 10 river basins over China, where the temperature breaking point gradually increases from northwest (17°C) to southeast (25°C).

FIG. 10. Different percentiles of I_h vs q and T .

This behavior suggests that the breaking point temperature depends on water vapor availability for the occurrence of precipitation and on the basin distance from the coast.

Based on data for 592 841 h at eight meteorological stations over China during 2000–15, we find that the breaking point temperature is also 25°C. When the temperature is lower than 13°C, precipitation extremes increase at a rate similar to the 1CC relation; this rate increases to a 2CC relation for 13°–25°C temperatures, then scaling decreases sharply with temperatures greater than 25°C.

We use the same scaling method to analyze the dependence of daily and hourly atmospheric humidity on temperature by analyzing relationships among R_h , e_a , q , and E_{pan} . We find that both daily and hourly temperature changes for extremes of e_a , q , R_h , and E_{pan} are accordant with that of precipitation extremes. Then we use the same method to analyze the daily and hourly precipitation extremes on atmospheric humidity by analyzing relationships between I_d and e_a and I_h and q . When e_a is lower than the breaking point, I_d exhibits a positive linear dependence on e_a , the correlation coefficient is not less than 0.98, and its corresponding breaking point temperature is 24.6°C. The q and T effect on I_h are very similar under the same percentile. Both daily and hourly precipitation extremes result from humidity control at the same temperature.

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APPENDIX

The Abbreviation of Variables in the Manuscript

CC	Clausius–Clapeyron
e_a	Actual vapor pressure (hPa)
e_s	Saturated vapor pressure (hPa)
E_{pan}	Pan evaporation (mm day^{-1})
I_d	Daily precipitation intensity (mm day^{-1})
I_h	Hourly precipitation intensity (mm day^{-1})
q	Specific humidity (g kg^{-1})
R_h	Relative humidity (%)

T	Daily mean temperature at 2-m height ($^{\circ}\text{C}$)
T_h	Hourly mean temperature at 2-m height ($^{\circ}\text{C}$)
$T_{d\max}$	Daily maximum air temperature at 2-m height in a day (2000–2000 Chinese standard time; $^{\circ}\text{C}$)
$T_{d\min}$	Daily minimum air temperature at 2-m height in a day (2000–2000 Chinese standard time; $^{\circ}\text{C}$)

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