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# Contrasting the responses of extreme precipitation to changes in surface air and dew point temperatures



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#### Abstract

The Clausius–Clapeyron (C–C) relationship is a thermodynamic relationship between saturation vapor pressure and temperature. Based on the C-C relationship, the scaling of extreme precipitation with respect to surface air temperature (i.e., extreme precipitation scaling) has been widely believed to quantify the sensitivity of these extremes to global surface warming under climate change. However, the extreme precipitation scaling rate in the observations produces counter-intuitive results, particularly in the tropics (i.e., strong negative scaling in the tropical land) possibly associated with limitations in moisture availability under the high-temperature bands. The trends in extreme precipitation based on station data are mixed with decreases in most of the tropics and subtropics and increases in most of the USA, western Europe, Australia, and a large portion of Asia. To try to reconcile these results, we examine the extreme precipitation scaling using dew point temperature and extreme precipitation and compare these results with those obtained from surface air temperature and extreme precipitation using station-based data, reanalysis data, and climate model simulations. We find that this mix of increases and decreases in the trends of extreme precipitation across the planet is more similar to the changes in surface dew point temperature rather than the actual temperature across the station-based data, reanalysis data, and the historical experiments with the National Center for Atmospheric Research (NCAR) Community Atmosphere Model, version 5 (CAM5). These findings suggest that dew point temperature is a better and more realistic metric for the responses of extreme precipitation to temperature increases. Therefore, the risk of having extreme precipitation is higher than what was obtained using surface air temperature, particularly in the tropics and subtropics (e.g., South Asia), areas of the world characterized by extremely high population density and severe poverty.

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#### 1 Introduction

Extreme precipitation is responsible for severe natural disasters including flooding, landslides, and debris flow leading to extensive socioeconomic impacts (e.g., Pielke Jr and Downton 2000; Schiermeier 2011). Understanding the changes in extreme precipitation under current and future climates is therefore of crucial importance (e.g., Alexander et al. 2006; Allan and Soden 2008; Lenderink and Van Meijgaard 2008; Min et al. 2011; O'Gorman 2015; Zhang and Villarini 2017; Zhang et al. 2007, 2017a, b; Sharma et al. 2018).

In this context, the extreme precipitation scaling with air temperature, based on the Clausius-Clapeyron (C-C) relationship (7%/°C), has been widely used to quantify the sensitivity of these extremes to surface warming under climate change (e.g., Allan and Soden 2008; Lenderink and Van Meijgaard 2010; O'Gorman and Schneider 2009; O'Gorman 2015; Park and Min 2017; Trenberth 2011; Zhang et al. 2017a). The C-C relationship, which represents the water holding capacity of the atmosphere, is a benchmark to interpret changes in extreme precipitation and global mean precipitation (Held and Soden 2006; O'Gorman 2015; Westra et al. 2014). Nonetheless, the deviation of scaling from the C–C relationship has been observed over many parts of the globe. For example, changes in precipitation intensity can be up to twice the C-C relationship for sub-daily extremes in the mid-latitudes (Lenderink and Van Meijgaard 2008; Lenderink et al. 2011; Westra et al. 2014). Moreover, in high-temperature regimes (e.g., above 24 °C) such as the tropics and sub-tropics, negative scaling rates are often observed, indicating a reduction in precipitation intensity with surface air warming (Bao et al. 2017; Chan et al. 2016; Maeda et al. 2012; Prein et al. 2017; Hardwick Jones et al. 2010; Utsumi et al. 2011; Wang et al. 2017; Wasko et al. 2016), inconsistent with the fact that the intensity and frequency of extreme precipitation has been rising (Alexander et al. 2006; Donat et al. 2016; Fischer and Knutti 2016) and projected to rise in the future (e.g., Kharin et al. 2007, 2013) over the majority of the globe. The spatial heterogeneity may result from the fact that temperature may not necessarily be the only factor determining available humidity as circulation changes can also be important. For extreme precipitation to scale at the C-C rate, relative humidity must remain constant (Lenderink and Van Meijgaard 2010; Lenderink et al. 2011; Wang et al. 2017). The inconsistency in the literature may also arise from different measures of extreme precipitation such as storm duration (Wasko et al. 2015) or even in the rarity of the extreme (Schär et al. 2016). At higher surface air temperatures, there tends to be limited relative humidity in the atmosphere, particularly in the tropics and middle latitudes (Lenderink et al. 2011; Utsumi et al. 2011; Wang et al. 2017; Westra et al. 2014). Such limitations in calculating the extreme precipitation scaling may be circumvented by using dew point temperature, which can reflect the changes of both relative humidity and surface air temperature (Lenderink and Attema 2015; Lenderink and Fowler 2017; Lochbihler et al. 2017). A few studies have found remarkable differences in the extreme precipitation scaling rate using surface air temperature and dew point temperature in some regions (e.g., Lenderink and Van Meijgaard 2010; Lenderink et al. 2011; Panthou et al. 2014; Ali and Mishra 2017; Ali et al. 2018; Wasko et al. 2018). Though, it is still unclear whether, the extent to which and in which regions the dew point temperature can outperform surface air temperature in representing the responses of extreme precipitation to surface warming.

Here, we aim to assess and quantify the usefulness of the scaling and the scaling of extreme precipitation with dew point temperature and to compare these results with those obtained using surface air temperature from a global perspective. We first analyze the trends in extreme precipitation using station-based data and then compare the trends with the scaling based on

the station-based data, reanalysis data, and model simulations. A global picture of such differences in scaling would allow us to better understand the changes in extreme precipitation in the current climate and the projection of precipitation extremes in the future, paving the way for the risk analysis of extreme precipitation and severe flooding.

#### 2 Data

The observations of daily surface air temperature, dew point temperature, and precipitation are obtained from the Global Surface Summary of the Day (GSOD) data (ftp://ftp.ncdc.noaa. gov/pub/data/gsod/). The GSOD data start from 1929, with data from 1973 to the present being the most complete. To substantiate the results based on the station-based GSOD data, we also use reanalysis data with global coverage and consistent spatial and temporal resolution by incorporating millions of observations into a stable data assimilation system. We use daily precipitation, surface air temperature and dew point temperature in the ERA-Interim reanalysis data set (Dee et al. 2011). Here we focus our analyses on the period 1979–2017, which represents the common period between ERA-Interim and the GSOD data.

The results from these datasets are complemented with the historical experiments by the finite volume dynamical core version of National Center for Atmospheric Research Community Atmosphere Model, version 5.1 (NCAR CAM5; Wehner et al. 2014). Data are obtained from the International CLIVAR C20C+ Detection and Attribution Project data portal at portal. nersc.gov/c20c (Folland et al. 2014). We obtained daily surface air temperature, precipitation and surface relative humidity from these experiments available with a spatial resolution of  $0.25 \times 0.25^{\circ}$ . Here we use the first ensemble member with all historical forcing (All-hist) for 1979–2005.

#### 3 Methods

We use Kendall's tau to quantify the trends in the intensity of extreme precipitation. More specifically, we first calculate the 99th/95th percentiles of daily precipitation in each year for the period 1979–2017 and then compute Kendall's tau to examine the presence of temporal trends in these percentiles. Note that different ways of choosing data may produce different results (e.g., Wasko and Sharma 2014; Molnar et al. 2015; Ali et al. 2018).

The scaling of extreme precipitation (*P*) with temperature (*T*, surface air temperature or dew point temperature) is based on the methodology used in previous studies (e.g., Hardwick Jones et al. 2010; Utsumi et al. 2011; Wasko et al. 2015):

$$\log(P) = \beta_0 + \beta_1 T \tag{1}$$

For each 0.5 K bin, we compute a high q percentile (e.g., the 99th percentile) for precipitation and this represents P; for the days exceeding P, we compute the median of the temperature and this represents T (e.g., Chan et al. 2016; Hardwick Jones et al. 2010; Lenderink and Van Meijgaard 2008; Utsumi et al. 2011; Wang et al. 2017; Zhang et al. 2017b). In each temperature bin, we should have at least 50 data points of precipitation to derive the 99th percentile of the distribution of precipitation. Rather than focusing on the rainy days, we consider all days of precipitation as done in previous studies (e.g., Schär et al. 2016; Wang et al. 2017). After estimating  $\beta_1$  through regression analysis, the scaling of precipitation ( $\Delta P\%$ ) with temperature is derived using an exponential transformation of the regression coefficients:

$$\Delta P\% = 100 \times \left(e^{\beta_1} - 1\right) \tag{2}$$

Given the fact that a negative scaling (e.g., peak structure) exists between extreme precipitation and air temperature in many regions across the globe (e.g., Drobinski et al. 2016, 2018; Wang et al. 2017), the method used here may not capture the peak structure between extreme precipitation and air temperature. By using this method (Eqs. 1–2), we aim to achieve fair comparisons in terms of the scaling between dew point temperature and extreme precipitation and the one between air temperature and extreme precipitation.

We calculate the extreme precipitation scaling using daily surface temperature, dew point temperature, and precipitation from the experiments with all observed historical forcing (Allhist) performed with NCAR CAM5 archived in the C20C+ Detection and Attribution Project with a quarter-degree spatial resolution (Folland et al. 2014). Dew point temperature at 2 m (DewPT) is calculated using daily surface temperature and relative humidity:

$$DewPT = \frac{257.14 \times Y}{18.678 - Y}$$
(3)

where

$$Y = \log \frac{\text{RH}}{100} + \frac{18.678 \times \text{Tas}}{257.14 + \text{Tas}}$$
(4)

in which RH represents relative humidity (%) while Tas is the surface air temperature (°C).

#### 4 Results

We use Kendall's tau to represent the trend in the magnitude of extreme precipitation in each year during the 1979–2017 period using the GSOD data. A strong increasing trend in the magnitude of extreme precipitation (defined as the 99th percentile) is observed in the USA, western Europe, Australia, and a large portion of Asia (e.g., the Philippines, North India, Japan, Korea), whereas a negative trend in extreme precipitation is located in the tropical Amazon, tropical Africa, Mexico, Eastern Europe, and northwestern China (Fig. 1a). The trend in extreme precipitation defined as the 95th percentile of daily precipitation over the same period is consistent with that using the 99th percentile, albeit with a weaker magnitude for the lower threshold over a large part of the globe (Fig. 1b). The trends in this study are similar to what reported in Westra et al. (2013), albeit having a larger region with positive trends in their study; this difference may arise from the fact that they examined the trends in precipitation during 1900–2009 while this study focuses on the study period 1979–2017. Overall, the spatial pattern of trends in extreme precipitation is consistent with previous observational studies (e.g., Asadieh and Krakauer 2015; Stocker et al. 2013). The meridional profile of trends in extreme precipitation averaged over longitudinal bands exhibits rising trends in the tropics and mid-latitudes (Fig. 2). The negative trends in the Polar Regions may be related to the limited number of stations there, leading to larger uncertainties (Fig. 2).



**Fig. 1** Kendall's tau for the intensity of the **a** 99th and **b** 95th percentile of daily precipitation in each year for the period 1979–2017. The dots in gray are for sites where the tau's value is not statistically significant while those in blue or red are for locations with statistically significant trends. The significance level is set at 5%

Given the spatial pattern of trends in extreme precipitation around the globe, it is of interest to examine whether the extreme precipitation scaling can reflect such changes in extreme precipitation over the period 1979–2017 because global surface has been warming over the recent decades (e.g., Houghton et al. 2001; Stocker et al. 2013). Figure 3 illustrates the extreme precipitation scaling rates using extreme precipitation, surface air temperature, and dew point temperature in the GSOD data. The extreme precipitation scaling rates using dew point temperature and extreme precipitation feature positive scaling in the vast majority of the globe except for some regions in the tropics (i.e., tropical Amazon and Africa), the Maritime Continent, western USA, Eastern Europe, and the Mediterranean. Overall, extreme



Fig. 2 Longitudinally averaged Kendall's tau of extreme precipitation (the 99th percentile of daily precipitation) using GSOD data. The buffer zones represent the 95% confidence intervals

precipitation scaling rates using dew point temperature and extreme precipitation (Fig. 3a) are consistent with the trends in extreme precipitation (Fig. 1), although there are some discrepancies in Eastern Europe with negative trends in extreme precipitation (Fig. 1a) and positive scaling rates (Fig. 3a). By contrast, the extreme precipitation scaling rates using surface air temperature and extreme precipitation are strongly negative in almost all the tropical regions,

the Mediterranean, Western Australia, Eastern Africa, and the western USA (Fig. 3b). The negative extreme precipitation scaling in the tropical land has been reported widely in the literature, probably associated with limited moisture availability in an environment with higher temperature (Utsumi et al. 2011; Wang et al. 2017; Wasko et al. 2016). Therefore, the extreme precipitation scaling rates using dew point temperature (Fig. 3a) seem to better capture the changes in extreme precipitation (Fig. 1a, b) than those using surface air temperature (Fig. 3b) in the period 1979–2017. This better representation of observed changes in extreme precipitation is due to the fact that dew point temperature explicitly accounts for the changes in relative humidity, which better reflects the responses of moisture in the atmosphere to surface warming. The dew point temperature sensitivities matched the extreme rainfall scaling that has been reported in previous efforts (e.g., Lenderink et al. 2011; Lenderink and Attema 2015; Bao et al. 2017; Wasko et al. 2018). The differences in the extreme precipitation scaling rates when using dew point and surface air temperature are large across the globe, with the strongest differences in the tropics (Fig. 3c). The differences between the extreme precipitation scaling based on dew point temperature and surface air temperature in India are consistent with previous studies (e.g., Lenderink and Van Meijgaard 2010; Lenderink et al. 2011; Panthou et al. 2014; Ali and Mishra 2017; Ali et al. 2018; Wasko et al. 2018), with a strong extreme precipitation scaling in India and particularly in Northern India: this is an area characterized by an extremely high population density (Im et al. 2017) and susceptible to significant socioeconomic impacts if the dew point temperature keeps on rising in the future.

To expand on the results using station-based GSOD data, we also examine the extreme precipitation scaling using dew point temperature and surface air temperature with ERA-Interim reanalysis data (Fig. 4). Overall, the extreme precipitation scaling rates using dew point temperature in ERA-Interim are consistent with those using GSOD, except in the southern USA and southern Australia. The extreme precipitation scaling using surface air temperature (Fig. 4b) is also consistent with those using GSOD data (Fig. 3b) with negative extreme precipitation scaling rates in the tropics and the western USA. However, there is a larger region with negative extreme precipitation scaling in the ERA-Interim data (Fig. 4b) compared with those based on GSOD data (Fig. 3b). The biggest differences in the two kinds of extreme precipitation scaling are located in the tropical land including South Asia, tropical Africa, South America, Mexico, Central America, and Australia (Fig. 4c), consistent with what found using the GSOD data (Fig. 3c).

The climate model simulation with CAM5 exhibits a similar pattern of extreme precipitation scaling rates as those in the GSOD data, with positive extreme precipitation scaling using dew point temperature almost everywhere (Fig. 5a) and negative extreme precipitation scaling in the tropics based on surface air temperature (Fig. 5b), with contrasting differences in the tropics, Australia, Mexico, and Central America (Fig. 5c). However, the differences in the extreme precipitation scaling rates (based on dew point temperature and surface air temperature) in CAM5 (Fig. 5c) are larger than those in the GSOD data (Fig. 3c). Moreover, the differences in extreme precipitation scaling using surface air temperature and dew point temperature (DewPT–TAS) in the ERA-Interim data are negative in most of the midlatitudes and polar regions while these differences are positive in the GSOD data and in the experiments with NCAR CAM5.

The meridional profiles of extreme precipitation scaling using dew point temperature and surface air temperature are distinct in the tropics and overall consistent beyond  $30^{\circ}$  N and  $50^{\circ}$  S (Fig. 6a). The extreme precipitation scaling using dew point temperature is positive within the  $50^{\circ}$  S– $50^{\circ}$  N band, while it is negative in the  $20^{\circ}$  S– $20^{\circ}$  N band based on surface air



Fig. 3 Extreme precipitation scaling rates (%/K) using a dew point temperature, b surface air temperature, and c their differences based on GSOD data. Extreme precipitation is defined as those events exceeding the 99th percentile



Fig. 4 Same as Fig. 3 but based on ERA-Interim data

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Fig. 5 Same as Fig. 3 but based on the historical experiments prescribing all the observed forcing (All-hist) with NCAR CAM5  $\,$ 



Fig. 6 Meridional profiles of longitudinally averaged extreme precipitation scaling rates for the responses of extreme precipitation to dew point temperature (red) and surface air temperature (blue) averaged over longitude in GSOD (a), ERA-Interim (b), and historical experiments with NCAR CAM5 (c). The buffer zones represent the 95% confidence intervals

 Table 1
 Global averaged extreme precipitation scaling rates (%/K) and their 95% confidence intervals using dew point and surface air temperature in GSOD, ERA-Interim and CAM5 historical experiments

	Precipitation and dew point scaling (%/K)	Precipitation and air temperature scaling (%/K)
GSOD ERA-Interim CAM5	$\begin{array}{c} 7.4 \pm 1.3 \\ 5.6 \pm 0.9 \\ 21.2 \pm 3.0 \end{array}$	$-6.3 \pm 1.6$ $-3.5 \pm 1.5$ $0.05 \pm 1.3$

temperature. The globally averaged extreme precipitation scaling over land using dew point temperature is 7.4%/K while it drops to -6.3%/K using surface air temperature (Fig. 6a; Table 1). The meridional profile of the extreme precipitation scaling rate in ERA-Interim shows positive scaling rate using dew point temperature and negative scaling rate using surface air temperature in the tropics, consistent with the GSOD data (Fig. 6b). Moreover, the global averaged extreme precipitation scaling rate using dew point temperature is 5.6%/K, compared with -3.5%/K using surface air temperature (Table 1). Note that the scaling rates shown in Table 1 are in good agreement with previous findings (Westra et al. 2013; Barbero et al. 2017a, b). Although the meridional profile of the extreme precipitation scaling using dew point temperature and surface air temperature in CAM5 experiments shows patterns similar to GSOD and ERA-Interim, the positive extreme precipitation scaling rate in the tropics in CAM5 (Fig. 6c) is much larger than GSOD and ERA-Interim (Fig. 6a, b). The global average extreme precipitation scaling rate using dew point temperature in CAM5 is 21%/K, which is much larger than what observed (Westra et al. 2013). Therefore, the extreme precipitation scaling rates using dew point temperature based on the GSOD data and ERA-Interim are similar to the C–C relationship  $(7\%)^{\circ}$  and are overestimated by CAM5 (21%/K); on the other hand, the extreme precipitation scaling rates using surface air temperature dramatically underestimate the C-C relationship across the GSOD data, ERA-Interim, and CAM5 (Table 1).

#### 5 Conclusion

The responses of extreme precipitation to temperature increases using dew point temperature and surface air temperature show contrasting results based on observations, reanalysis data, and climate model simulations. Overall, the extreme precipitation scaling rates using extreme precipitation and dew point temperature can better represent the observed increase in the magnitude of extreme precipitation using the GSOD data, likely due to explicitly accounting for relative humidity in the calculation of dew point temperature.

The extreme precipitation scaling rates using dew point temperature are distinct from those using surface air temperature, with higher values almost globally and opposite results in the tropics (e.g., South Asia, tropical Amazon, and Africa), across the station-based data, reanalysis data, and the historical experiments with the NCAR CAM5. The global average extreme precipitation scaling rate with station-based data using dew point temperature is 7.4%/K while it drops to -6.3%/K using surface air temperature; the results based on ERA-Interim are comparable, with 5.6%/K and -3.5%/K when using dew point and surface air temperature, respectively. These findings suggest that dew point temperature is a better and more realistic indicator of the response of extreme precipitation to temperature increases.

This study also highlights the need to better represent dew point temperature in the climate simulations and the need to use dew point temperature to calculate the extreme precipitation scaling rate, especially in the tropics, consistent with previous studies (Barbero et al. 2017a, b; Lenderink et al. 2018). The extreme precipitation scaling rate using dew point temperature may reflect more realistic responses of extreme precipitation to the ongoing global warming.

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