Barbero R, Westra S, Lenderink G, Fowler HJ.

Temperature-extreme precipitation scaling: A two-way causality?

International Journal of Climatology 2017

DOI link to article:

https://doi.org/10.1002/joc.5370

Date deposited:

31/01/2018

Embargo release date:

05 December 2018

Temperature-extreme precipitation scaling: a two-way causality?

R. Barbero[a b *] S. Westra[c] G. Lenderink[d] H. J. Fowler [a]
[a] School of Engineering, Newcastle University, Newcastle-upon-Tyne, United-Kingdom
[b] Irstea, Mediterranean Ecosystems and Risks, Aix-en-Provence, France
[c] School of Civil, Environmental and Mining Engineering, University of Adelaide, Adelaide, Australia
[d] Royal Netherlands Meteorological Institute, De Bilt, The Netherlands

*Correspondence to: renaud.barbero@irstea.fr

Extreme precipitation events are widely thought to intensify in a warmer atmosphere through the Clausius-Clapeyron equation. The temperature-extreme precipitation scaling was proposed to analyze the temperature dependency of short-duration extreme precipitation and since then, the concept has been widely used in climatology. Bao *et al.* (2017) (Nature Climate Change, DOI:10.1038/NCLIMATE3201) suggest that the apparent scaling reflects not only how surface air properties affect extreme precipitation, but how synoptic conditions and localised cooling due to the storm itself affect the scaling – implying two-way causality. We address here critical issues of this paper and provide evidence that dew point temperature drives extreme precipitation, with the direction of causality reversed only for the storm's peak intensity. This physical inference may serve as a basis to better quantify scaling rates and to help establish the relationship between extreme precipitation and environmental conditions in the current climate, and thereby provide insights into future changes to precipitation extremes due to climate change.

Key Words: precipitation extreme; temperature-extreme precipitation scaling; dew point temperature; Australia; climate change;

Received . . .

1. Introduction

In a recent paper (Nature Climate Change, DOI:10.1038/NCLIMATE3201), Bao *et al.* (2017) study future changes to precipitation extremes in Australia under a warming climate using a regional climate model with parameterised convection. They report on projections of a uniform increase in precipitation extremes across Australia, including the northern half of the country where there is a negative historical scaling relationship between temperature and extreme precipitation (Hardwick Jones *et al.* 2010; Herath *et al.* 2017), in agreement with what is generally observed in tropical regions (Utsumi *et al.* 2011; Maeda *et al.* 2012; Wasko *et al.* 2016). While the moisture-holding capacity of the atmosphere is expected to increase with surface temperature through the Clausius-Clapeyron (CC) equation (Pall *et al.* 2007), the negative scaling observed in tropical regions is generally attributed to limitations in atmospheric moisture at higher temperatures (Hardwick Jones *et al.* 2010; Westra *et al.* 2014), particularly at extreme precipitation percentiles and for longer storm durations (Wasko *et al.* 2015). In contrast, Bao *et al.* (2017) attribute the negative historical apparent scaling relationship to lower temperatures associated with storms which arise from local saturated downdraughts and evaporative cooling of the rain itself and from synoptic atmospheric properties such as colder air found generally in low-pressure systems. Thus they suggest that the apparent scaling reflects not only how surface air properties affect extreme precipitation, but also how atmospheric conditions that are correlated with precipitation affect surface air properties – implying two-way causality. The idea that the atmosphere drives air surface temperature as well as precipitation (i.e., wet conditions favor less sunshine and more evaporative cooling) is not new and previous findings indicate that neither temperature nor precipitation should be interpreted without considering their strong covariability (Trenberth and Shea 2005). This mutual control is often observed across various time scales and under favorable circulation patterns, antecedent high sea surface temperature may enhance evaporation and provide additional moisture for coastal areas (Lenderink *et al.* 2009), implying a lagged relationship between temperature and precipitation. Previous work has examined how scaling results can be altered by a temporary localised cooling in air surface temperature associated with precipitation extremes by considering air mass properties during but also a few hours before the shower (Lenderink *et al.* 2011), with Bao *et al.* (2017) suggesting that this will shift

*Corresponding author: renaud.barbero@irstea.fr many events to lower daily temperature bins. As the magnitude of the 'cooling effect' is linked to event size, the largest precipitation events will cause the greatest local cooling, and thus move into lower temperature bins, leading to a reduction or reversal in the theoretical Clausius-Clapeyron scaling. If, as the authors claim, this is the primary reason for negative scaling relationships observed in tropical regions, then the historical scaling would be an irrelevant concept with which to examine future changes to precipitation extremes, at least in the tropical zone.

We argue here that the first-order driver of the apparent negative scaling relationship observed at Darwin is not a temporary localised cooling in surface air temperature associated with precipitation extremes as proposed in Bao *et al.* (2017). Instead, using quality controlled data from the meteorological station at Darwin Airport (ID 014015, 130.89°E-12.42°S) providing both temperature and precipitation data from 1954-2007, we show that i) the cooling effect shown in Bao *et al.* (2017) can be obtained simply as an artefact of data sampling based on the temporal autocorrelation of synoptic systems, ii) positive scaling is obtained when the dew point temperature coincident to the precipitation day (which reflects the actual amount of moisture in the atmosphere) is used as a scaling variable and iii) short-duration (hourly) precipitation extremes intensify with increased dew point temperature for hours preceding the peak intensity; a cooling effect due to the storm itself is evident only during the peak intensity of the storm.

2. Results and discussion

Bao *et al.* (2017) illustrate the cooling effect in Darwin with a composite analysis of observed temperature spanning from 7-days before to 7-days after extreme precipitation days grouped into different temperature bins, which are ordered based on the temperature on the day of the storm. They conclude that the cooling effect coincident with extreme precipitation may move these events to colder temperature bins in the precipitation scaling diagram, thereby reducing the apparent scaling (see Figure 2a in their paper). This effect is thought to dominate precipitation scaling in tropical regions, where the temperature range across the year is small. Repeating the analysis of Bao *et al.* (2017) at Darwin using 10 temperature bins, we found similar results (Figure 1a). However, since temperature at a given time-step is correlated with temperature at the previous and subsequent time steps, we would expect that temperature would return to the average daily temperature for that month as we extend backward and forward in time simply as a result of the autocorrelation properties of the time series commonly observed in atmospheric synoptic conditions. We illustrate this statistical property of autocorrelated data in a simple example where the temporal pattern of daily temperature observed at Darwin is replicated using a time series (N=10,000) with μ=0, σ=1, and the same skewness and lag-1 autocorrelation as the original data. The synthetic time series is then stratified by quantile (from 0.1 to 1) based on the synthetic temperature on the central day (lead/lag=0). We show the temporal evolution of temperature before and after the values observed in each quantile in Figure 1b. As expected, the elapsed time before returning to normal conditions increases for the extreme quantiles, indicating that the so-called cooling effect for the coldest bin is in fact a regression to the mean effect, and can be reproduced with a simple autoregressive model on the synthetic 'temperature' time series (i.e. ignoring covariability with other variables such as preciptation). The asymmetry between warm and cold temperature bins is due to the negative skewness of the observed temperature time series (Figure 1c). This skewness reduces the probability of sampling a cold day before or after a wet day in the coldest bin: not surprising given that wet days are generally cooler than dry days. Consequently, wet days in the warmest bins hardly exceed the climatological temperature while wet days in the cold bins strongly deviate from the climatology. We therefore conclude that, although the most intense precipitation events in Darwin are often fed by low pressure systems which cause cold air advection that may move some associated extreme precipitation events to lower temperature bins, the temporal temperature profile shown in Bao *et al.* (2017) reflects the statistical properties of autocorrelated temperature data (and does not prove that the most intense precipitation events are systematically displaced to colder bins), can be reproduced by the nature of the sampling and does not provide information on the presence or direction of causality between extreme rainfall and temperature.

Bao *et al.* (2017) use surface air temperature as a scaling variable for precipitation extremes, as do most recent studies (Wang *et al.* 2017). However, atmospheric moisture scales with surface air temperature only under the assumption of constant relative humidity (Lenderink and van Meijgaard 2010) and it is well known that such conditions are not prevalent at high temperatures in the tropics (Hardwick Jones *et al.* 2010). Instead, we argue that dew point temperature (estimated by cooling air at constant pressure until saturation occurs) provides a more robust estimate of the amount of moisture available in the atmosphere since by definition a 1°C increase in the dew point temperature is equal to an approximately 7% moisture increase in the atmosphere (Lenderink and van Meijgaard 2010; Lenderink *et al.* 2017). We examined how precipitation extremes change with both air surface temperature and the dew point temperature using a quantile regression method that estimates a regression model at the tail (here the 99th percentile) of the conditional distribution. This approach has proven to be unbiased with respect to sample size along the temperature range (Wasko and Sharma 2014). While surface air temperature on the same day as the precipitation event scales negatively with daily precipitation depth (Figure 2,top) (note that using temperature before the storm reduces this negative scaling but does not reverse the sign), dew point temperature on the same day provides a positive scaling (Figure 2,bottom) that even slightly exceeds the CC relation. Indeed, as air surface temperature increases, deviation from dew point temperature increases (Figure 3). This deviation leads to a decrease in relative humidity and precipitation depth, indicating that humidity in the atmospheric boundary layer does not increase proportionately to air surface temperature. In this case, the only way for a warm air parcel to reach saturation is to rise and cool down until it saturates at high altitude. When the air parcel saturates, the maximum water vapor content in the atmosphere is actually lower than what we would expect from air surface temperature as it overestimates the actual temperature at condensation (Drobinski *et al.* 2016). Note that dew point temperature gives the humidity at cloud base assuming a non-entraining ascent. Additionally, moisture that transits over Darwin is generally picked up over the ocean and hence sea surface temperature might in this case be a better proxy for available moisture in the atmosphere. We therefore propose that a decrease in relative humidity at higher air temperatures is more likely the first-order driver of the negative scaling relation in Darwin. This historical relationship between dew point temperature and extreme precipitation is not necessarily inconsistent with future increases in extreme precipitation as reported in Fig 3c in Bao *et al.* (2017) and confirms previous results indicating that expected increases to precipitation extremes in response to global warming are primarily based on the expected moisture increase (Lenderink and Attema 2015). The dew point temperature thus appears as a legitimate avenue of investigating how precipitation extremes might change in the future.

Finally, although the Bao *et al.* (2017) analysis was based on daily precipitation data, localised cooling associated with precipitation events can occur quite rapidly. Now we use sub-daily data to better understand the processes underlying the mutual causality of precipitation extremes and dew point temperature over shorter timescales. Hourly precipitation extremes are generally more sensitive to day-to-day dew point temperature variations (Drobinski *et al.* 2016; Schroeer and Kirchengast 2017) and are expected to intensify at a faster rate than daily extremes in a warmer climate (Prein *et al.* 2016). We found that >91% of 1-h rainfall extremes in Darwin (defined as >95th percentile of wet hours) were embedded within short-duration (<12-hour) storms. We performed composite analyses and estimated the mean dew point temperature and air surface temperature (available as three-hourly data) centered on the 1-h peak intensity of short-duration storms. Both air surface temperature and dew point temperature reveal a short-term cooling effect due to the storm itself (as opposed to the gradual cooling over several days seen in Bao *et al.* (2017)) during its peak intensity (the larger the peak, the stronger the cooling effect) but the dew point temperature shows a warming effect spanning from 72 hours to 3 hours before the peak intensity (the stronger the warming effect, the larger the peak intensity), a period during which atmospheric water content is increasing (Figure 4). This indicates that i) dew point temperature controls the magnitude of short-duration storms, while the storm itself induces a cooling effect only during the peak intensity and ii) the cooling effect from the storm is unlikely to affect significantly scaling results for short-duration storms when using daily average dew point temperature and/or maximum dew point temperature within a day.

3. Concluding remarks

Results reported in Bao *et al.* (2017) raise two fundamental questions in the context of climate change: (i) Which variable comes first in the temperature-extreme precipitation scaling relationship? (ii) Can this scaling method accurately represent the influence of warming on extreme precipitation? Their results indicate that observed scaling based on surface air temperature is not reflective of future changes in precipitation extremes over Australia. We agree with this statement and have shown here that changes in relative humidity are the likely first-order drivers of the historical negative scaling found between air temperature and extreme precipitation in Darwin. This highlights the need to include moisture, in the form of dew point temperature, in the scaling relation and we would recommend that all further scaling studies consider its strong role.

While possible feedbacks between atmospheric conditions and surface air temperature may confound the scaling relation, we have provided evidence that dew point temperature drives short-duration extreme precipitation, with the direction of causality reversed only for the storm's peak intensity. This physical inference may serve as a basis to better quantify scaling rates and to help establish the relationship between extreme precipitation and environmental conditions in the current climate (Zhang *et al.* 2017), and thereby provide insights into future change to precipitation extremes due to climate change. Further research is clearly needed to better explain the role of local factors versus large-scale circulation drivers on temperature-precipitation scaling (Pfahl *et al.* 2017) and this may help to elucidate whether or not future changes in precipitation extremes are likely to exceed observed scaling rates estimated through dew point temperature variations.

Acknowledgement

This work was supported by the INTENSE project. INTENSE is supported by the European Research Council (grant ERC-2013-CoG-617329). Hayley Fowler is funded by the Wolfson Foundation and the Royal Society as a Royal Society Wolfson Research Merit Award holder (grant WM140025). Seth Westra is supported by Australian Research Council Discovery project DP150100411.

References

Bao J, Sherwood SC, Alexander LV, Evans JP. 2017. Future increases in extreme precipitation exceed observed scaling rates. *Nature Climate Change* **7**(2): 128–132, doi:10.1038/nclimate3201, URL http://www.nature.com/doifinder/10.1038/nclimate3201.

Drobinski P, Alonzo B, Bastin S, Da Silva N, Muller C. 2016. Scaling of precipitation extremes with temperature in the French Mediterranean region: What explains the hook shape? *Journal of Geophysical Research: Atmospheres* **121**(7): 3100–3119, doi:10.1002/2015JD023497.

Hardwick Jones R, Westra S, Sharma A. 2010. Observed relationships between extreme sub-daily precipitation, surface temperature, and relative humidity. *Geophysical Research Letters* **37**(22): 1–5, doi:10.1029/2010GL045081.

Herath SM, Sarukkalige R, Nguyen VTV. 2017. Evaluation of empirical relationships between extreme rainfall and daily maximum temperature in Australia. *Journal of Hydrology* : 1–11doi:10.1016/j.jhydrol.2017.01.060, URL http://dx.doi.org/10.1016/j.jhydrol.2017.01.060.

Lenderink G, Attema J. 2015. A simple scaling approach to produce climate scenarios of local precipitation extremes for the Netherlands. *Environmental Research Letters* **10**(8): 085 001, doi:10.1088/1748-9326/10/8/085001, URL http://stacks.iop.org/1748-9326/10/i=8/a=085001?key=crossref.96eded874798c5917444728a95abbd1d.

Lenderink G, Barbero R, Loriaux J, Fowler H. 2017. Super-Clausius-Clapeyron scaling of extreme hourly convective precipitation and its relation to large-scale atmospheric conditions. *Journal of Climate* **30**(15), doi:10.1175/JCLI-D-16-0808.1.

Lenderink G, Meijgaard E, Selten F. 2009. Intense coastal rainfall in the Netherlands in response to high sea surface temperatures: Analysis of the event of August 2006 from the perspective of a changing climate. *Climate Dynamics* **32**(1): 19–33, doi:10.1007/s00382-008-0366-x.

Lenderink G, Mok HY, Lee TC, Van Oldenborgh GJ. 2011. Scaling and trends of hourly precipitation extremes in two different climate zones - Hong Kong and the Netherlands. *Hydrology and Earth System Sciences* **15**(9): 3033–3041, doi:10.5194/hess-15-3033-2011.

Lenderink G, van Meijgaard E. 2010. Linking increases in hourly precipitation extremes to atmospheric temperature and moisture changes. *Environmental Research Letters* doi:10.1088/1748-9326/5/2/025208.

Maeda EE, Utsumi N, Oki T. 2012. Decreasing precipitation extremes at higher temperatures in tropical regions. *Natural Hazards* **64**(1): 935–941, doi: 10.1007/s11069-012-0222-5.

Pall P, Allen MR, Stone DA. 2007. Testing the Clausius-Clapeyron constraint on changes in extreme precipitation under CO2 warming. *Climate Dynamics* **28**(4): 351–363, doi:10.1007/s00382-006-0180-2.

Pfahl S, OGorman PA, Fischer EM. 2017. Understanding the regional pattern of projected future changes in extreme precipitation. *Nature Climate Change* **7**(6): 423–427, doi:10.1038/nclimate3287, URL http://www.nature.com/doifinder/10.1038/nclimate3287.

Prein AF, Rasmussen RM, Ikeda K, Liu C, Clark MP, Holland GJ. 2016. The future intensification of hourly precipitation extremes. *Nature Climate Change* **7**(1): 48–52, doi:10.1038/nclimate3168, URL http://www.nature.com/doifinder/10.1038/nclimate3168.

Schroeer K, Kirchengast G. 2017. Sensitivity of extreme precipitation to temperature: the variability of scaling factors from a regional to local perspective. *Climate Dynamics* **0**(0): 0, doi:10.1007/s00382-017-3857-9, URL http://link.springer.com/10.1007/s00382-017-3857-9.

Trenberth KE, Shea DJ. 2005. Relationships between precipitation and surface temperature. *Geophysical Research Letters* **32**(14): 1–4, doi:10.1029/2005GL022760.

Utsumi N, Seto S, Kanae S, Maeda EE, Oki T. 2011. Does higher surface temperature intensify extreme precipitation? *Geophysical Research Letters* **38**(16): 1–5, doi:10.1029/2011GL048426.

Wang G, Wang D, Trenberth KE, Erfanian A, Yu M, Bosilovich M, Parr DT. 2017. The peak structure and future changes of the relationships between extreme precipitation andtemperature. *Nature Climate Change* **7**(4): 268–274, doi:10.1038/nclimate3239, URL http://www.nature.com/doifinder/10.1038/nclimate3239.

Wasko C, Parinussa RM, Sharma A. 2016. A quasi-global assessment of changes in remotely sensed rainfall extremes with temperature. *Geophysical Research Letters* doi:10.1002/2016GL071354.

Wasko C, Sharma A. 2014. Quantile regression for investigating scaling of extreme precipitation with temperature. *Water Resources Research* doi:10.1002/2013WR015194.

Wasko C, Sharma A, Johnson F. 2015. Does storm duration modulate the extreme precipitation-temperature scaling relationship? *Geophysical Research Letters* **42**(20): 8783–8790, doi:10.1002/2015GL066274, URL http://doi.wiley.com/10.1002/2015GL066274.

Westra S, Fowler HJ, Evans JP, Alexander LV, Berg P, Johnson F, Kendon EJ, Lenderink G, Roberts NM. 2014. Future changes to the intensity and frequency of short-duration extreme rainfall. *Reviews of Geophysics* **52**(3): 522–555, doi:10.1002/2014RG000464, URL http://doi.wiley.com/10.1002/2014RG000464.

Zhang X, Zwiers FW, Li G, Wan H, Cannon AJ. 2017. Complexity in estimating past and future extreme short-duration rainfall. *Nature Geoscience* **10**(4): 255–259, doi:10.1038/ngeo2911, URL http://www.nature.com/doifinder/10.1038/ngeo2911.

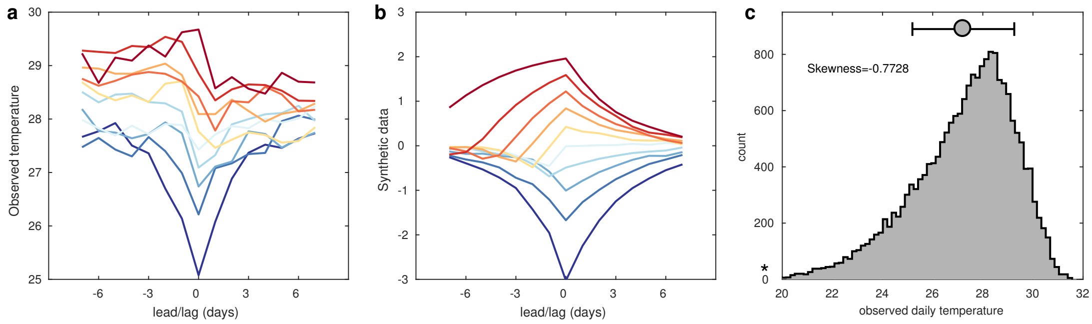

Figure 1. a) Daily mean temperature observed in Darwin spanning 7 days before to 7 days after extreme precipitation events. Different colours from darkest blue (coolest) to darkest red (warmest) represent the 10 different temperature bins. b) Same as Figure 1a but using a time series (N=10,000) with =0, =1 and the same skewness and first-order autocorrelation observed in Darwin. The synthetic time series is then stratified into 10 bins by quantile (from 0.1 to 1) and its temporal evolution before/after the values observed in each quantile is shown. c) Distribution of observed daily temperature illustrating the negative skewness of the data. The horizontal line (boxplot) indicates the overall mean, as well as the standard deviation of the distribution.

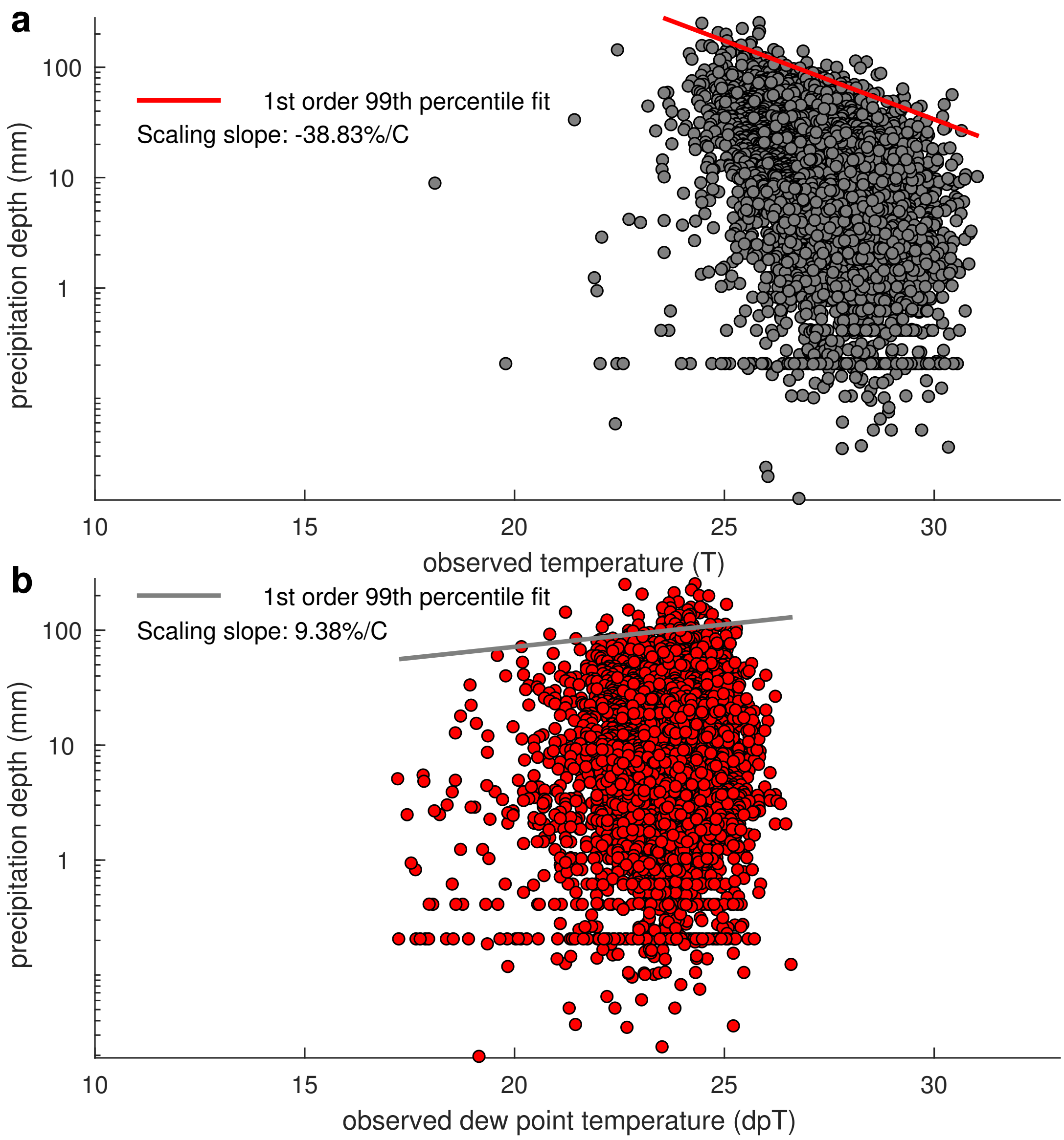

Figure 2. Estimation of the scaling slopes for the 99th percentile of wet days through a quantile regression method using both (a) daily air surface temperature and (b) daily dew point temperature. Slopes for air surface temperature (red line) and dew point (grey line) are shown and their magnitudes in percent of warming degree are reported.

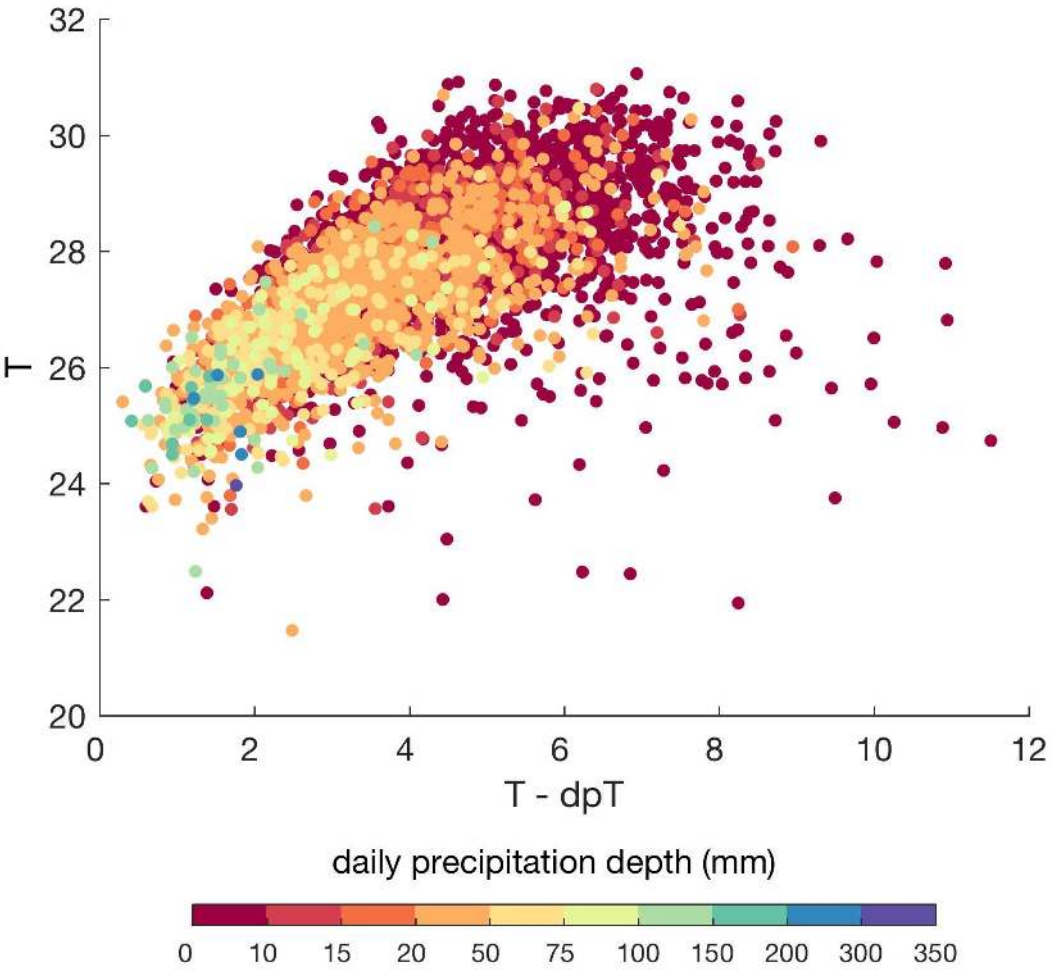

Figure 3. Relationships between daily air surface temperature (y-axis), the deviation of daily air surface temperature from daily dew point temperature (x-axis) and daily precipitation depth (color). Note that the color scale is not linear.

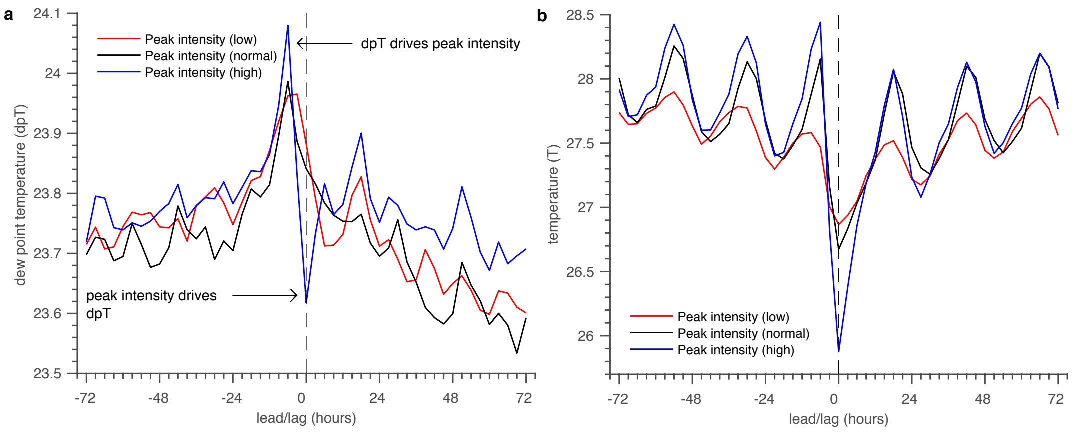

Figure 4. 3-hour a) dew point temperature and b) air surface temperature blocks observed in Darwin spanning 72 hours before to 72 hours after the peak intensity of short-duration storms (¡12 hours). The peak intensity is defined as the maximum 1-hour burst within each storm. Storms were classified as follows: storms with the lower one-third peak intensity (low), middle one-third peak intensity (normal) and upper one-third peak intensity of the distribution of the maximum 1-hour burst of each storm.