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Geophysical Research Letters

RESEARCH LETTER
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Resolving Inconsistencies in Extreme Precipitation-Temperature Sensitivities

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Key Points:
- Correct sampling of dry-bulb temperature before storm events resolves inconsistencies in extreme precipitation-temperature sensitivities
- Previous underestimation of sensitivities is likely due to localized cooling and intermittent nature of precipitation
- Dry-bulb temperature drives short-duration precipitation extremes, contrary to previous dew point temperature based findings

Supporting Information:
- Supporting Information S1

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Abstract Extreme precipitation events are intensifying with increasing temperatures. However, observed extreme precipitation-temperature sensitivities have been found to vary significantly across the globe. Here we show that negative sensitivities found in previous studies are the result of limited consideration of within-day temperature variations due to precipitation. We find that short-duration extreme precipitation can be better described by subdaily atmospheric conditions before the start of storm events, resulting in positive sensitivities with increased consistency with the Clausius-Clapeyron relation across a wide range of climatic regions. Contrary to previous studies that advocate that dew point temperature drives precipitation, dry-bulb temperature is found to be a sufficient descriptor of precipitation variability. We argue that analysis methods for estimating extreme precipitation-temperature sensitivities should account for the strong and prolonged cooling effect of intense precipitation, as well as for the intermittent nature of precipitation.

Plain Language Summary Increasing global temperatures are likely to result in the intensification of extreme precipitation events with resultant flooding of great societal concern. Understanding the relationship between extreme precipitation and temperature provides valuable information for the design, operation, and risk assessment of high-hazard infrastructure. However, the observed precipitation-temperature relationship has been found to vary significantly across the globe, with negative relationships found in warmer climatic regions. Using station-based subdaily observations, we show that careful sampling of higher temperatures measured before the start of the storm events can result in positive extreme precipitation-temperature relationships across a wide range of climatic regions. Dry-bulb temperature is found to drive short-duration precipitation extremes, contradicting previous studies promoting dew point temperature as the main driver of precipitation variability. Our results indicate the use of coarser daily-scale observations in previous studies contributed to obtaining negative relationships by limiting consideration for within-day temperature variation caused by the rainfall event itself.

1. Introduction

Expected intensification of extreme precipitation due to a warming climate is of considerable societal concern, with resultant floods being one of the most common, dangerous, and destructive natural disasters (FitzGerald et al., 2010; Hallegatte et al., 2013; Johnson et al., 2019). Extreme precipitation events have been found to be increasing in both observations (Guerreiro et al., 2018; Martinez-Villalobos & Neelin, 2018; Peleg et al., 2018; Wasko & Nathan, 2019a; Westra et al., 2013) and climate models over the past six decades (Donat et al., 2016; Kendon et al., 2014, 2017). The primary physical reasoning for the future increase in extreme precipitation events is the increase of atmospheric water vapor as governed by the Clausius-Clapeyron (CC) relation at an approximate rate of 6–7%/°C. There has thus been great interest in exploring the relationship between observed precipitation extremes and (near) coincident temperature, which may infer how precipitation extremes and dominant precipitation mechanisms will change with increasing temperatures (Lenderink & Attema, 2015; Lenderink & van Meijgaard, 2008). However, inconsistent and spatially varying extreme precipitation-temperature sensitivities have been found across the world, including many regions showing negative sensitivities (Maeda et al., 2012; Utsumi et al., 2011; Wasko, Parinussa, et al., 2016).

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Reasons given for the occurrence of negative sensitivities include (1) moisture limitations at higher temperatures (Barbero et al., 2018; Hardwick Jones et al., 2010; Roderick et al., 2019), (2) localized cooling associated with extreme precipitation and prestorm synoptic conditions (Ali & Mishra, 2017; Bao et al., 2017), and (3) pooling of storm events with limited consideration for intraseasonal variation in temperature (Ali et al., 2018; Berg et al., 2009). This has led to the development of multiple conceptual frameworks for calculating precipitation-temperature sensitivities distinguishing on season (Berg et al., 2009), storm duration (Panthou et al., 2014; Wasko et al., 2015), and storm type (Molnar et al., 2015). However, inconstancies in sensitivity results remain, questioning dry-bulb temperature's representativeness of the atmospheric state causing the increase in precipitation extremes.

Various alternatives to surface dry-bulb temperature have been proposed. The use of atmospheric temperatures instead of surface temperatures has showed modest improvement (Ali & Mishra, 2017; Bui et al., 2019; Golroudbary et al., 2019). Alternatively, the relationship between atmospheric water vapor has also been examined (Neelin et al., 2009; Roderick et al., 2019; Schiro et al., 2016), resulting in sensitivities more consistent with climate model predictions of future rainfall intensification (Roderick et al., 2020). However, by far, the replacement of surface dry-bulb temperature with surface dew point temperature is the most common variable substitution, with results shower greater consistency with the CC relation (Ali et al., 2018; Ali & Mishra, 2017; Barbero et al., 2018; Lenderink & van Meijgaard, 2010; Park & Min, 2017; Wasko et al., 2018). The improved robustness of dew point results is often framed alongside improved process understanding, implicating dew point temperature (moisture availability) as the primary driver of extreme precipitation, with the assertion that it is a better measure of increases in the moisture holding capacity of the atmosphere causing the increase in precipitation extremes (Lenderink et al., 2011, 2018). However, dew point temperature sensitivities often remain inconsistent with observations and model studies (Barbero et al., 2017; Wasko & Nathan, 2019b; Zhang et al., 2019), with added discrepancies between daily and subdaily extreme precipitation sensitivity results (Wasko et al., 2018).

Most frameworks investigating observed precipitation-temperature sensitivities have relied on ground-based precipitation and temperature data that are readily available at daily time scales. Understanding changes to subdaily rainfall extremes is however becoming more and more important, with increasing evidence that higher temperatures can lead to more extreme precipitation over shorter subdaily time scales (Lenderink & van Meijgaard, 2008; Panthou et al., 2014; Wasko et al., 2015; Westra et al., 2014) and changes to the temporal and spatial distribution of rainfall (Lochbihler et al., 2017; Wasko, Sharma, et al., 2016; Wasko & Sharma, 2015). Stronger (more positive) sensitivities for subdaily precipitation extremes compared to daily extremes have been attributed to the complex interplay of atmospheric processes at a daily scale (Lenderink & van Meijgaard, 2008) and the underestimation of daily extremes due to the intermittent nature of precipitation (Schleiss, 2018; Utsumi et al., 2011).

Even when temperature observations are available at a subdaily temporal scale, they are generally converted to daily averages for calculation of precipitation-temperature sensitivities (Hardwick Jones et al., 2010). This averaging obscures periods of rapid cooling associated with extreme precipitation events or early onset cooling of precursor synoptic conditions (Ali et al., 2018; Bao et al., 2017). Thus, daily mean temperature values might not be representative of the atmospheric state associated with the precipitation extreme. For example, Ali and Mishra (2017) found that negatives sensitivities in India can be reversed by pairing rainfall intensities with the daily mean dry-bulb temperature 1 to 3 days before the rainfall event. Lenderink et al. (2011) showed that more consistent extreme precipitation-temperature sensitivities can be obtained across a temperature range using dew point temperature a few hours prior to the precipitation event, compared to daily mean dry-bulb temperature. However, temperature sampling strategies remain largely arbitrary.

We believe valuable can be inferred from extreme precipitation sensitivity where the key predictor variable is carefully sampled to be representative of the atmospheric state causing the increase in precipitation extremes. Here we examine temperature's role in the physical processes underlying the causality of precipitation extremes at a subdaily scale to inform rainfall event selection and representative temperature sampling. We aim to answer the following question: Is the observed extreme precipitation-temperature sensitivity more consistent with the CC relation when sampled temperatures are representative of the precipitation causing atmospheric state?

2. Data and Methods

2.1. Meteorological Data

Data were obtained from the Bureau of Meteorology of Australia. Precipitation is measured using either pluviographs or tipping buckets at 6-min intervals and is available for 1,489 stations across Australia. Precipitation observations less than 0.02 mm were considered to be 0. Subdaily measurements of dry-bulb temperature (simply referred to as temperature) and dew point temperature are available from 1,829 and 1,574 synoptic stations respectively, where recording resolution varies from twice daily up to eight measurements a day. Due to the low precision (0 decimals) of many dew point temperature measurements, higher precision dew point records were constructed using actual vapor pressure (e_a) derived from psychrometric data as described in Text S1 in the supporting information (Allen et al., 1998; Lucas, 2010; World Meteorological Organization [WMO], 2018). Our analysis was therefore restricted to stations with measurements of both subdaily precipitation and dry-bulb temperature, with higher precision dew point values derived for stations with measurements of wet-bulb temperature and atmospheric pressure. Analysis was also restricted to sites that have >10 years of record and have <25% missing data. These data selection criteria yielded 385 qualifying stations, 250 of which had reconstructed dew point records, distributed across Australia covering a wide range of climatic types (Crosbie et al., 2012).

2.2. Selection of Rainfall Events

In practice, two precipitation events are considered independent if they are separated by a specified time period of zero precipitation, referred to as the interevent (IE) time (also event separation time). Various IE times have been used in previous studies ranging from 1 hr (Wasko et al., 2018), 2 hr (Gaál et al., 2014; Molnar et al., 2015), up to 5 hr (Wasko & Sharma, 2014), resulting in unique subsets of selected rainfall events, impacting the derived precipitation-temperature sensitivities. Figure 1 presents four sampling strategies for rainfall event selection.

Using an IE time of 1 hr (Figure 1a) results in the selection of two rainfall events (E1 and E2). E1 is a shorter intense continuous rainfall burst (20 mm/hr), while E2 is a longer-duration highly intermittent event. The 1-hr peak precipitation intensity for E2 (7 mm/hr) occurs during the latter part of the event, likely at a reduced temperature due to the preceding rainfall. An IE time larger than 1 hr (Figure 1b) results in the selection of a single rainfall event (E1). Event E1 consists of a continuous burst of rainfall at the start followed by a dry period with lower intermittent rainfall toward the end of the event. Figures 1a and 1b show how larger IE times can result in event selection excluding secondary precipitation bursts by stringing shorter-duration bursts together.

We propose two novel event separation alternatives (Figures 1c and 1d). The use of a smaller IE times isolates a larger number of highly efficient continuous precipitation bursts (Figure 1c). The smallest possible value for the IE time is limited to the recording resolution of the precipitation data, that is, 6 min (or 0.1 hr). However, we would generally assume that events separated by a minimum period of 6 min of zero rainfall will not be statistically independent (E2 and E3 in Figure 1c). A time period requirement of zero precipitation before the event start can thus be imposed (Figure 1d) resulting in the selection of continuous precipitation events (E1 and E2 in Figure 1d). This specified dry period prior to precipitation events will limit the impact of the localized cooling effect on (near) coincident temperature sampling.

The maximum 1 hr of precipitation within the event was selected for analysis to represent peak precipitation intensity. For events that do not persist for 1 hr, the peak precipitation intensity was taken as the total accumulated hourly precipitation. Events with average precipitation intensity of less than 0.2 mm/hr and a peak intensity less than 1 mm/hr were omitted. Additionally, events with very short durations, less than or equal to 18 min, were also omitted.

2.3. Construction of Precipitation-Temperature Pairs

The 1-hr peak precipitation intensity of each selected event needs to be matched to a temperature. The method proposed by Lenderink and van Meijgaard (2008) to determine sensitivity relationships for hourly precipitation with daily mean temperature has been widely used. This method extracts maximum precipitation intensities for a given duration for each wet day and then pairs the precipitation with the daily mean (or maximum) temperature. The maximum precipitation intensity is typically extracted over the same daily

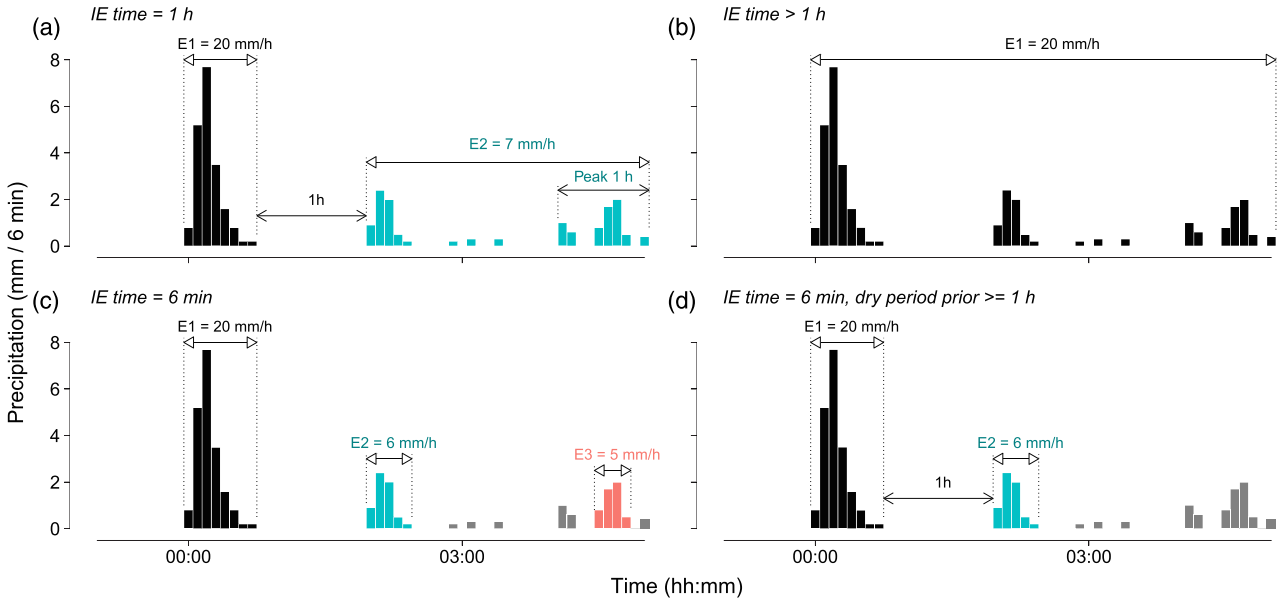


Figure 1. Rainfall event selection strategies and corresponding 1-hr peak precipitation intensity selected using an IE time (a) equal to 1 hr, (b) larger than 1 hr, (c) equal to the rainfall measurement interval of 6 min, and (d) equal to the rainfall measurement interval of 6 min with a minimum required dry period before the event of 1 hr. Different colored shading denotes different selected events (E#), where gray shading indicates nonqualifying rainfall. The 1-hr peak precipitation intensity per selected event is indicated in mm/hr.

period terminating at a specified time (such as 09:00 a.m.) to correspond with the calculation of mean (or maximum) daily temperatures (Blenkinsop et al., 2015). However, this allows for potential interruption of intradiurnal precipitation events. To capture the atmospheric state before the start of storm events we propose each precipitation event is paired with the 24 hr, 12 hr, and 6-hr mean temperature and mean dew point temperature before the event start. To compare to previously adopted temperature sampling strategies, each precipitation event was also paired with the 24-hr mean temperature and mean dew point temperature centered around the time of max precipitation intensity.

2.4. Calculation of Sensitivity

Often, studies investigate precipitation-temperature sensitivities by binning the data into temperature ranges, referred to as binning techniques (Pumo et al., 2019). In this study, sensitivity was calculated using quantile regression (Koenker & Bassett, 1978), which has been shown to yield estimates that are more unbiased and robust compared to binning techniques (Wasko & Sharma, 2014). Quantile regression was computed using the R package "quantreg" (Koenker, 2018). The sensitivity of peak precipitation intensity (P) with temperature (T) was calculated using Equation 1:

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

where q is the target quantile and β_0 and β_1 are fitted parameters. The sensitivity ($\Delta P\%$) of peak precipitation intensity with temperature as a percentage was calculated through an exponential transformation of the slope of the fitted quantile regression relationship, β_1^q, using Equation 2:

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

3. Results

3.1. Sensitivity to 24 hr (Prior) Versus 24 hr (Centered) Temperature

Figure 2 presents the calculated sensitivity for the 99th nonexceedance percentile 1-hr peak precipitation intensity with temperature and dew point temperature for stations across Australia, using the baseline IE

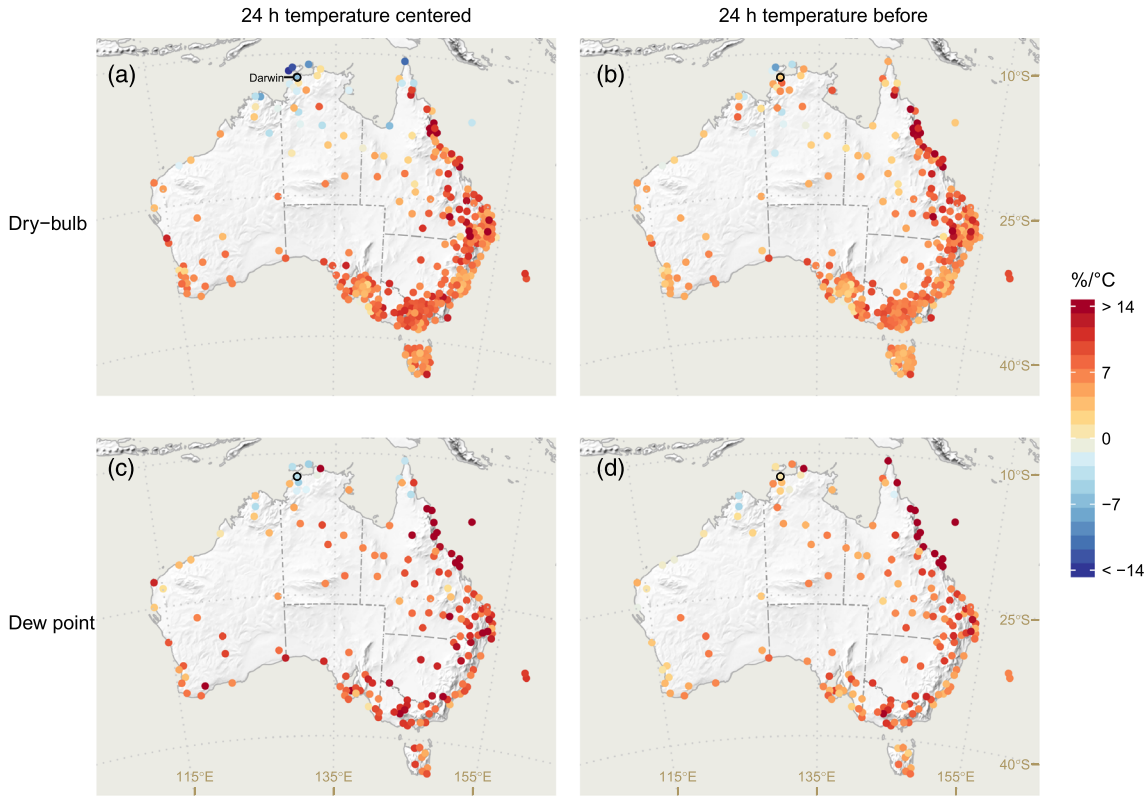


Figure 2. Sensitivity of 99th percentile 1-hr peak precipitation intensity to dry-bulb and dew point temperatures across Australia: (a) 24-hr mean dry-bulb temperature centered around peak intensity, (b) 24-hr mean dry-bulb temperature before start of storm event, (c) 24-hr mean dew point temperature centered around peak intensity, and (d) 24-hr mean dew point temperature before start of storm event. Minimum requirement of 750 events per station. Darwin Airport station (ID 014015) indicated as Darwin.

time of 1 hr (Figure 1a). With the use of 24-hr mean temperature centered around the time of peak intensity (Figure 2a), positive sensitivities occur across most of the country with slightly elevated values along the northeast coastline. Negative sensitivities can be seen for many stations in the northern tropical regions dominated by convective regimes. The interquartile range of sensitivity values across Australia is 5.1–9.0%/°C, with overall trends in precipitations sensitivities comparable to those presented in Hardwick Jones et al. (2010) and Wasko et al. (2018).

Using 24-hr mean temperatures before the start of the event (Figure 2b) results in markedly different sensitivities across Australia then when a 24-hr mean centered on the event is used. Figure 2b reveals a lower and narrower sensitivity interquartile range of 4.6–8.0%/°C. Many of the stations that exhibited negative sensitivities in the tropics now exhibit positive values, with only a few stations demonstrating slight negative to neutral values. A negative sensitivity reversal (−6.6%/°C to 2.7%/°C) can be seen for tropical meteorological station at Darwin Airport (ID 014015). The results suggest that sampling temperature over the peak precipitation results in a negative sensitivity in the tropics due to cooling by the storm, and a temperature prior to the start of precipitation better represents the atmospheric conditions related to the storm event. Exceptions remain predominantly along the northeastern coastline and a few other isolated locations that greatly exceed CC.

Using dew point temperature does not resolve inconsistencies in results, and the lower data availability is evident through the reduced number of qualifying stations (Figures 2c and 2d). Hence, the focus remains on (dry-bulb) temperature, and for dew point-based results the reader is referred to the supporting information. We note that dew point temperature sensitivities in the northeast and central inland areas, categorized by low annual rainfall, are found to be more consistent with the CC relation compared to dry-bulb temperature sensitivities. This shift in the performance of the predictor variable appears to coincide with the

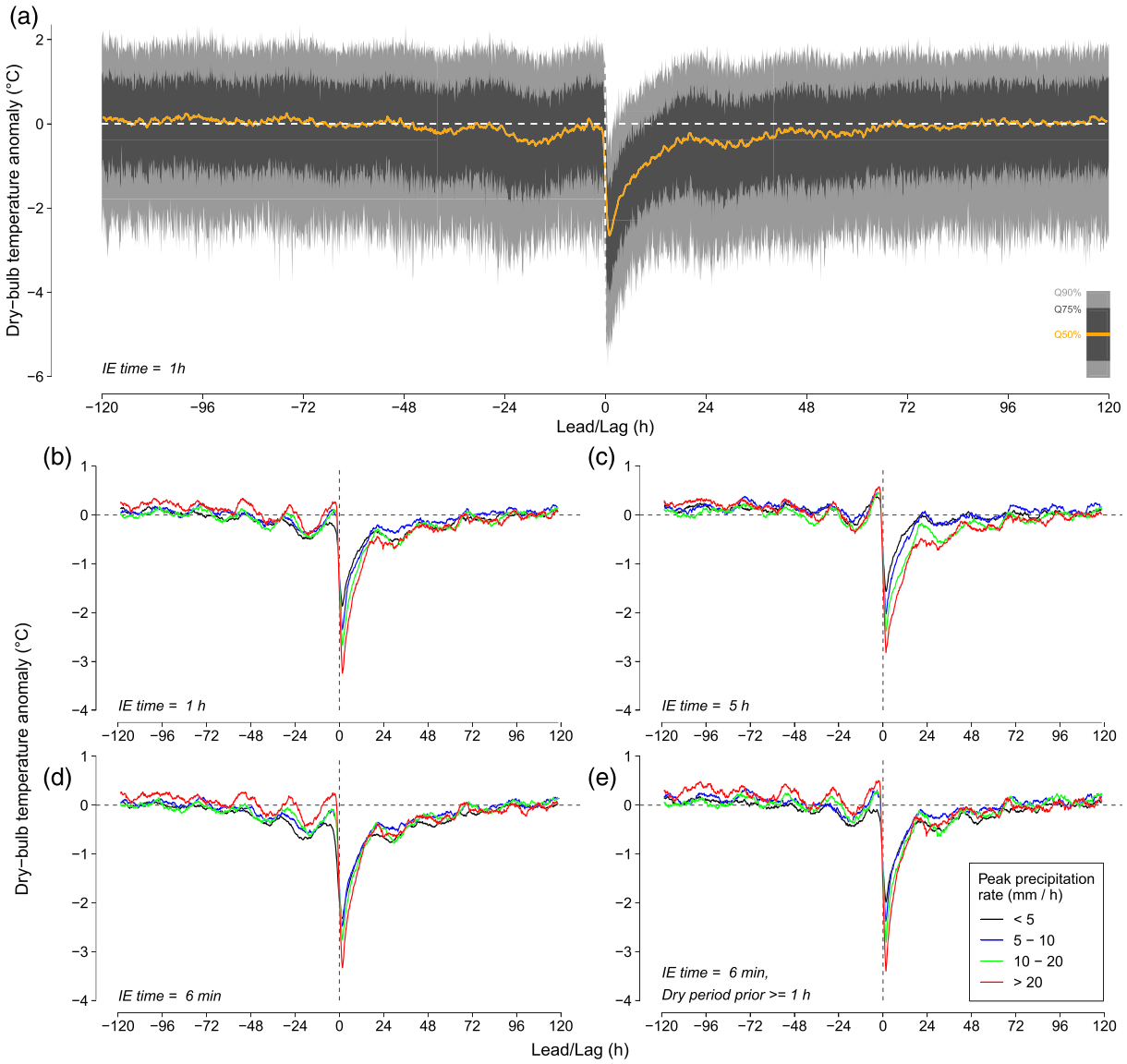


Figure 3. (a) Quantile ranges of observed dry-bulb temperature anomaly from the average subdaily day-of-year temperature in Darwin spanning 120 hr before to 120 hr after precipitation events. (b–e) Q50 median dry-bulb temperature anomaly of storm events classified on peak precipitation intensity. Results are presented for selected storm events using an IE time of (a and b) 1 hr, (c) 5 hr, (d) 6 min, and (e) 6 min with minimum 1-hr dry period before the event start.

transition of dominant storm mechanism (convective along the tropical coastline to frontal systems requiring greater inland penetration). The use of smaller 12- and 6-hr sampling periods before the start of the storm event (Figure S1) results in similar sensitivities compared to a 24-hr strategy for both temperature and dew point temperature.

3.2. Temperature Anomaly Before/After Event Start

To understand the difference in sensitivity results between temperature sampling methods, we performed a composite analysis using data from the tropical meteorological station at Darwin Airport (ID 014015) to estimate temperature anomalies before/after the start of precipitation events (Figure 3a). All precipitation events are centered on event start time (0 hr) with observed temperature anomalies calculated for 120 hr before/after the event start. Dew point temperature anomaly results are consistent with those presented here (Figure S2 and Text S2).

In Figure 3a, the median temperature anomaly (orange line) indicates slight cooling in the lead up to events from approximately −48 to −18 hr, followed by a rise in temperature up to the event start (0 hr). A clear sharp decrease in temperature is experienced at the start of precipitation, followed by a slower recovery back to the expected temperature. Sampling mean temperature values that include precipitation, for example, a 24-hr sample period centered around the time of peak precipitation intensity, will include periods of rapid cooling associated with extreme precipitation events or early onset cooling of precursor synoptic conditions and not be representative of the atmospheric state associated with the precipitation extreme. If higher intensity precipitation events result in greater magnitude cooling, the storm event will further reduce contributing to negative precipitation-temperature sensitivities (Bao et al., 2017). Figure 3b presents the median temperature anomaly per selected peak precipitation intensity category using an IE time of 1 hr. The results confirm largely stratified temperature anomalies across selected precipitation intensity categories, with the highest intensity category (>20 mm/hr) associated with the largest anomaly leading up to the event start, as well as the largest magnitude temperature drop after.

The 24-hr period before the event start appears to be an appropriate sample range to utilize as a temperature predictor for precipitation intensity with good distinction between peak precipitation rate categories. This sampling strategy also mitigates the issues associated with temperature reductions due to the event itself but, in turn, can be influenced by localized cooling associated with preceding precipitation and prestorm synoptic conditions. An approach to limit the effects of previous rainfall events is the use of larger IE times, but this approach has multiple drawbacks (see section 2.2) including the creation of longer-duration events strung together by prolonged periods of high intermittency rainfall, with the potential to result in elevated temperatures compared to a continuous rainfall event over the same time period. To understand how selected associated temperature anomalies might vary with choice of IE time, Figures 3c–3e present temperature anomalies based on the IE strategies presented in Figure 1.

The use of a larger IE time of 5 hr (Figure 3c) increases the required period of zero precipitation between events and thus increase the likelihood no precipitation occurred in the preceding hours. The result is elevated and less stratified temperature anomalies in the preceding days, with a sharp temperature increase before the event start. Compared to Figure 3b, there is no significant difference in the magnitude of temperature drop and temperature recovery is prolonged. This occurs because a longer IE time predominantly selects the first precipitation event after a longer dry period, while "stringing" secondary precipitation bursts together within the same event (see Figure 1b).

The use of the smallest possible IE of time of 6 min (Figure 3d) results in the selection of all continuous precipitation bursts. The amplification of temperature before the start of the event is lower but more stratified, followed by a faster temperature recovery period. This is due to many previously considered secondary precipitation bursts now being included, with an increased probability of being preceded by rainfall and a reduced probability of being succeeded by additional bursts. When an independence requirement of 1 hr of zero rainfall prior to the event is imposed (Figure 3e), the temperature anomalies prior to the event start are elevated with reduced stratification compared to Figure 3d. Figures 3e and 3b represent the same independence requirement of 1 hr of zero rainfall before an event start, the key difference being the strict selection of continuous rainfall events in Figure 3e, while intermittent rainfall events are included in Figure 3b.

3.3. Change in Sensitivity Based on IE Time

To present the influence of IE sampling time on precipitation-temperature sensitivity countrywide results are presented in Figures 4a–4c using the IE approaches identified in Figures 1b–1d. Results are compared against the baseline 1-hr IE approach with a 24-hr temperature prior to the event (Figure 2b), where any differences can be attributed to the IE approach adopted. A performance metric was calculated as the change in absolute difference of the sensitivity from the expected 7% value, that is, does the evaluated IE approach result in sensitivity values closer or further away from the expected value of 7% compared to the baseline approach. Results of the performance assessment are presented in Figures 4d and 4e. Inferences gained from dew point temperature results (Figure S3) provide no additional insights due to reduced data availability.

Using the longer IE time of 5 hr (Figure 4a) results in a reduced number of precipitation events and thus fewer qualifying stations. An overall reduction in sensitivity values can be seen compared to baseline (Figure 2b), with a resultant lower sensitivity interquartile range of 3.9–7.8%/°C. There is a notable

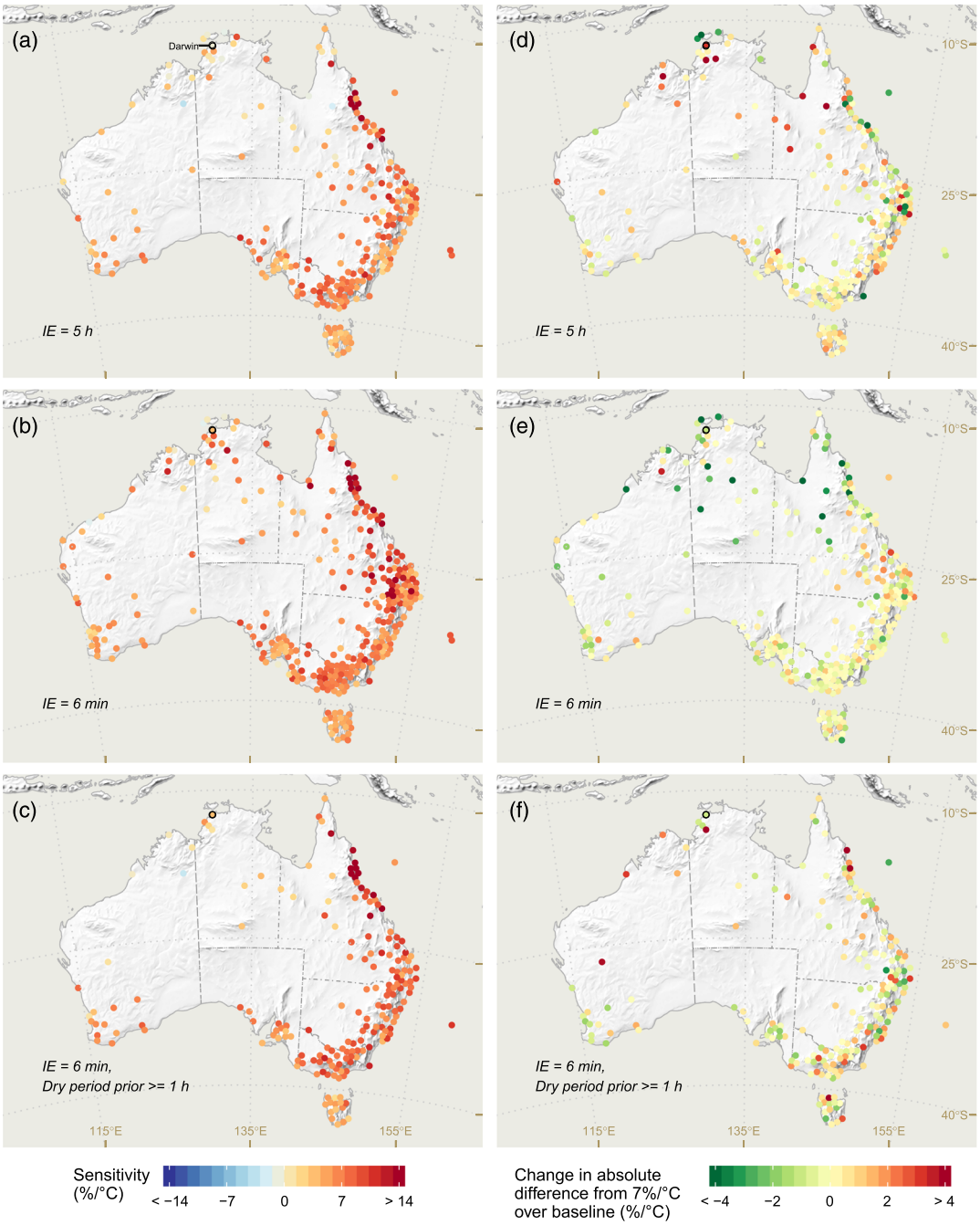


Figure 4. (a–c) Sensitivity of 99th percentile 1-hr peak precipitation intensity with 12-hr mean dry-bulb temperature before start of storm event. (d–f) Change in absolute difference of calculated sensitivity from 7%/°C compared to baseline (Figure 2b) with negative (green) values indicating improved consistency with the expected CC relation. Results presented based on use of IE times of (a, d) 5 hr, (b, e) 6 min, and (c, f) 6 min with minimum 1-hr dry period before event start. Minimum requirement of 750 events per station.

reduction in the sensitivity value for Darwin (from 1.2%/°C to −0.5%/°C). Comparison against baseline results (Figure 4d) shows overwhelmingly positive (yellow to red) across Australia indicating larger inconsistency of sensitivity values with the expected CC relation.

The smallest IE time of 6 min (Figure 4b) allows for the selection of all continuous rainfall events, increasing the number of selected events and qualifying stations across Australia. An overall increase in sensitivity values compared to baseline is evident with an interquartile range of 5.1%/°C to –8.4%/°C, close to the CC

relation. This increase is particularly evident in the tropics and inland areas showing overwhelmingly green stations with improved performance over baseline (Figure 4e). The sensitivity for Darwin increases from a baseline value of 1.2–3.9%/°C. An imposed dry period requirement of 1 hr before the event start (Figure 4c) results in a significant reduction of the number of qualifying stations. This indicates that continuous precipitation bursts are more likely to be preceded by rainfall compared to intermittent events as included in the baseline IE approach. The sensitivity interquartile range is elevated to 5.4–8.9%/°C, very close to the CC relation. The sensitivity value for Darwin is 3.7%/°C, slightly lower compared to no dry period imposed. Performance comparison (Figure 4f) delivers mixed results, with no clear regional trends due to the limited number of qualifying stations. The superior countrywide performance of Figure 4b suggests the inclusion of preceding temperature depressions are representative of the atmospheric state causing secondary continuous precipitation bursts.

4. Conclusions

The results show that observed extreme precipitation-temperature sensitivities are more consistent with the CC relation when a subdaily temperature representative of the atmospheric conditions prevailing the storm event is considered. The use of daily observations, longer IE times and mixed selections of continuous and intermittent precipitation events contributed to inconsistent sensitivities found in previous studies. We further conclude the following:

1. In tropical regions, where previous studies found negative precipitation-temperature sensitivities, the use of dry-bulb (or dew point) temperatures just prior to precipitation results in positive sensitivities.
2. Temperature sampling strategies should consider the strong and prolonged cooling effect of precipitation events, which is more pronounced in the tropics.
3. Methods used in precipitation event selection can result in selection of longer-duration events with high intermittency while ignoring secondary precipitation bursts, resulting in lower sensitivities compared to continuous precipitation events.
4. In general, with increasing dry periods before an event start (lower moisture availability), precipitation-temperature sensitivities decrease due to weaker performance of temperature predictor as indicator of the atmospheric state causing the precipitation.

As dry-bulb temperature is found sufficient for the calculation of precipitation-temperature sensitivities, it can be concluded that dry-bulb temperature variations are a driver of precipitation intensity. Dew point temperature sensitivities are only found to be more consistent with the CC relation in limited inland locations categorized by low moisture availability. The shift in predictor performance appears to coincide with the transition of dominant storm mechanism (convective along the tropical coastline to frontal systems requiring greater inland penetration).

Positive extreme precipitation-temperature sensitivities can be obtained in the tropics using dry-bulb temperature data without the addition of covariates or seasonal normalization of observed data as used in previous studies, providing an improved conceptual framework for studying how precipitation will change in a warming climate. An implication of these results is the immediate increase in data availability compared to data subsets or alternate observed climatic variables such as dew point temperature, allowing for easier extension of analyses worldwide. The use of a shorter IE time based on the precipitation recording resolution (6 min in this study) is recommended to ensure selection of continuous precipitation events. The imposition of a zero-precipitation period prior to the event start can be incorporated to better ensure independence between events; however, this comes at the expense of the number of qualifying events.

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Data Availability Statement

Data were obtained from the Australian Bureau of Meteorology and can be found online (at http://www.bom.gov.au/climate/data/stations/).

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