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RESEARCH ARTICLE

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Diverging trends in US summer dewpoint since 1948

Jacob Scheff | **James Cody Burroughs**

Department of Geography and Earth Sciences, University of North Carolina, Charlotte, North Carolina, USA

Correspondence
Jacob Scheff, Department of Geography and Earth Sciences, University of North Carolina, 9201 University City Blvd., Charlotte, NC 28223, USA.
Email: jscheff@uncc.edu

Abstract

Increases in summer humidity are a basic threat to human survival, because the body cannot shed heat by sweating if absolute humidity is too high. However, climate change trends and patterns of extreme humidity have been much less studied than those of extreme temperature. Here, using station data, we provide an up-to-date and comprehensive assessment of the patterns and 1948–2020 trends of summertime dewpoint (T_d) in the contiguous United States, for multiple percentiles of its distribution ranging from median to extreme. We find that summer-median T_d is maximized in the Southeast and along the coasts, while extreme summer T_d is counterintuitively higher in the Midwest than in much of the Southeast, and is higher in Western agricultural valleys than on the Pacific coast. In contrast, 1948–2020 trends in summer T_d are broadly consistent across percentiles, but quite divergent regionally. Namely, median and extreme T_d have strongly increased in Florida, South Texas, parts of California and from the Northeast to the Northern Plains, but have declined in the Intermountain West and changed little elsewhere, often despite clear summertime warming. These regional T_d non-increases contradict basic theory, but agree with several recent studies. In addition, median T_d is increasing more systematically than extreme T_d in several parts of the eastern United States. Future work will seek to uncover the reasons for all of these divergences and to better understand the fate of summer humidity worldwide.

KEYWORDS

climate change, dewpoint, humidity, summer, trends

1 | INTRODUCTION

1.1 | Why dewpoint?

Absolute or specific humidity is one of the most impactful weather measurements on the human body, because it strongly constrains the rate at which sweat can evaporate and shed the body's metabolic heat. When ambient humidity is significantly lower than the saturation humidity over human skin, sweat can evaporate into the air, transferring latent heat from the body to the air. However, if ambient humidity approaches or exceeds skin humidity, then net vapour transfer from the skin to the environment becomes inefficient or impossible, preventing the body from cooling in this way (e.g., Coffel et al., 2018; Sherwood & Huber, 2010) and therefore risking heatstroke and death. Even before those more acute outcomes are reached, warming of the skin forces the heart to work much harder to transfer metabolic heat to the skin, increasing the incidence of cardiovascular and lung disease (e.g., Kjellstrom et al., 2015).

Because core body temperature must be maintained near 37°C (98.6°F), skin temperature must stay at least a few degrees lower than this to allow the heart to easily transfer metabolic heat. So, skin humidity during sweat can be no more than the saturation humidity at ~35°C (~95°F). This means that the dewpoint T_d, which quantifies the ambient humidity q using its saturation temperature,

$$q = q_{\text{sat}}(T_d), \tag{1}$$

is a natural indicator of the efficiency of latent cooling (e.g., McKinnon & Poppick, 2020). If T_d is much less than ~35°C, the body-air q gradient is large and sweat can easily cool the body, but the closer T_d gets to ~35°C, the more inefficient this process becomes. T_d values above ~32°C are rare today, but some subtropical regions can experience T_d ~30°C, especially in South and East Asia and in the Persian Gulf (Freychet et al., 2020; Im et al., 2017; Raymond et al., 2020), with severe health and mortality impacts (e.g., Coffel et al., 2018).

Several other humidity-related metrics are also used in the context of human overheating and/or comfort. In popular English, "% humidity" or relative humidity (RH) is often used to convey how humid the air feels. However, this metric is not relevant for the evaporation of sweat, because it is calculated relative to the saturation humidity of the *air* (with its variable temperature) rather than the skin (~35°C). This is why a cool rainy winter day with 100% humidity does not feel muggy, but a hot sunny summer day with 50% humidity does: the latter has much larger *absolute* humidity and thus its T_d is closer to the skin's limit of ~35°C.

Conversely, the wet-bulb temperature T_w, which is the coolest temperature an air parcel can attain by evaporating water into it, is thought to be the ultimate driver of human thermal comfort in much of the climate-change literature (e.g., Coffel et al., 2018; Im et al., 2017; Raymond et al., 2020; Sherwood & Huber, 2010). This is because T_w has a one-to-one relationship with the air's total latent and *sensible* energy, that is, its total enthalpy,

$$c_p T + Lq = c_p T_w + L q_{\text{sat}}(T_w). \tag{2}$$

Thus the skin-air T_w gradient indicates the total ability of the skin to cool by turbulent transfer of both temperature and moisture. Since skin T_w can be no more than ~35°C by the above arguments, the proximity of ambient T_w to 35°C is often thought to be the most basic indicator of human thermal stress.

In humid climates, however, T_d is the dominant control on T_w. Substituting Equation (1) into Equation (2) and letting $s = dq_{\text{sat}}/dT$ at some T_i between T_d and T_w, we have

$$T_w = \frac{s}{s + (c_p/L)} T_d + \frac{(c_p/L)}{s + (c_p/L)} T. \tag{3}$$

That is, T_w is a weighted average of T_d and T, with s and (c_p/L) the respective weights. $(c_p/L) \approx 0.41\,\text{g}\cdot\text{kg}^{-1}\cdot\text{K}^{-1}$, but by the Clausius–Clapeyron equation, $s \approx q_{\text{sat}}(T_i) * 0.07\ \text{K}^{-1}$. In humid climates with $T_d > 20°\text{C}$ and thus $q_{\text{sat}}(T_i) > q_{\text{sat}}(T_d) > 16\ \text{g}\cdot\text{kg}^{-1}$, we have $s > 1.12\,\text{g}\cdot\text{kg}^{-1}\cdot\text{K}^{-1}$, much larger than (c_p/L). Therefore T_w will lie much closer to, and be more strongly controlled by, T_d than T. For example, on a hot, humid Southeastern US day with $T = 35°\text{C}$ and $T_d = 24°\text{C}$, $T_w \approx 27°\text{C}$ (Brice & Hall, 2022).

This is the main reason why T_d has such a key role in extreme human heat stress, and why we focus on it here. Vecellio et al. (2022) found using human trials that T plays a larger role in reality than implied by the above, as the skin never becomes saturated, and in fact more traditional heat-stress metrics like the heat index (table 5 of Steadman, 1979) depend almost equally on T and T_d in humid conditions. Nevertheless, we focus on T_d here, as trends in T extremes are thoroughly explored in the literature but trends in T_d and its extremes are barely examined (e.g., Seneviratne et al., 2021). T_d is also stable with respect to the diurnal cycle and is directly measured by weather stations, making it more useful and convenient than other humidity measures (McKinnon & Poppick, 2020). Finally, since T cannot fall below T_d, high T_d values can force overnight T to stay elevated, preventing the body from cooling off nocturnally and leading to dangerous health outcomes (e.g., Kjellstrom et al., 2015).

As the planet warms due to greenhouse gas emissions, we expect q and therefore T_d (1) to generally increase, since $q = q_{\text{sat}}(T) * \text{RH}$, and RH is not expected to change much (e.g., Held & Soden, 2006; Schneider et al., 2010). From all of the above, this should have negative impacts on human health. However, it is often unclear what controls the most extreme T_d readings and trends, which have the strongest impacts. Therefore, we carefully review the prior literature on these phenomena.

1.2 | Observed dewpoint extremes and trends

For the Midwestern United States, Bentley and Stallins (2008) examined nine widespread extreme summer T_d

events between 1960 and 2000, including the infamous July 1995 heat/humidity wave that took hundreds of lives in Chicago and elsewhere in the region (Kunkel et al., 1996). They found that these events had three key ingredients: (1) high antecedent rainfall and soil moisture which enhanced crop and soil evapotranspiration, (2) a low-level ridge propagating into the region and (3) a resulting capping inversion, which kept the boundary layer shallow and trapped the evapotranspired moisture near the surface. In short, Bentley and Stallins (2008) found that local factors were most often important for extreme T_d in the Midwest, despite occasional roles for larger-scale factors like moisture advection from the Gulf of Mexico. Although urban heat islands can increase T significantly, and did so in the 1995 Chicago event, Kunkel et al. (1996) found that urban T_d during that event was actually *lower* than rural T_d, confirming the key role of evapotranspiration for the extreme T_d. Critically, Changnon et al. (2006) found that extreme T_d events in this region increased significantly over the course of the 1960–2000 period.

In contrast, Robinson (2000) obtained relatively weak summertime mean T_d trends in the United States during 1951–1990, with just slight increases in the central part of the country (including the Midwest) and minimal trends elsewhere. However, they did not examine extremes. Interestingly, Robinson (2000) also analysed US T_d trends outside of summer, finding widespread increases in spring T_d and declines in winter T_d. However, these would not be expected to be as relevant for human health (due to the much lower baseline), so are outside the scope of this study. Finally, Robinson (2000) found that all of the above trends were quite sensitive to the start date, with much more positive trends obtained for 1961–1990 than for 1951–1990, consistent with Changnon et al. (2006) above. This suggests the importance of using as long a reliable record as possible, so as to truly capture the long-term climate-change response rather than internal decadal variability.

Indeed, Brown and DeGaetano (2013) found broadly similar results to Robinson (2000) using a 1947–2010 study period, including increases in spring T_d, especially in the central United States, and decreases in winter T_d, especially in the southeast United States, with little overall change in annual T_d and rather inconsistent changes in summer and/or annual-maximum T_d. However, during the more recent 1980–2010 period, Brown and DeGaetano (2013) found much stronger summer T_d increases, especially in central and eastern parts of the country, again consistent with Changnon et al. (2006). In contrast, T_d decreases dominated from 1947 to 1979 and continued in the western United States even after 1980.

McKinnon et al. (2021) confirmed these surprising long-term interior-western summer T_d declines, particularly in the southwest and particularly on hot days (but also in the mean). They tentatively attributed them to declines in soil moisture and evapotranspiration, in a region where moisture advection from outside is hindered by high topography. Williams et al. (2014) pointed out that these anomalously low summer T_d values were a critical factor in the disastrous 2011 western wildfire season, as they played a key role in widening the vapour pressure deficit (the difference between the actual and saturation vapour pressures) which is the main control on fuel moisture.

Brown and DeGaetano (2013) also usefully reviewed the changes in T_d instrumentation that took place in the United States over the decades, and evaluated their potential impact on trends. Originally psychrometers were used, but these were replaced with dial hygrometers in the 1960s, then with chilled mirror hygrometers in the 1980s, and finally with Vaisala humidity sensors in the 2000s. However, they found that these changes did not influence the trends in a systematic fashion, so the trends are still meaningful. Indeed, we find (below) that stations in the same climatic region usually have quite similar trends, so measured T_d trends are likely dominated by real T_d changes rather than by these instrument changes, particularly at regional and larger scales. Our time series are also largely free of sudden jumps (below), corroborating this conclusion.

Freychet et al. (2020) examined extreme summertime T_w events and their trends in station data from China from 1979 to 2017. They found critical roles for both elevated T and T_d, even though T_d has the stronger numerical influence as shown above. T_w exceeded 29°C in many southeast China events, even reaching 31°C on one occasion. These events were clearly increasing in frequency, particularly when defined in terms of the daily minimum; though interestingly for the United States and Canada Schwartzman et al. (1998) found that daily maximums of summer T_d had increased more strongly than minimums.

More broadly, and alarmingly, Raymond et al. (2020) found that the frequencies of T_w exceeding 27, 29, 31 and 33°C have each more than doubled globally since 1979, with the highest occurrences in South Asia, the coastal Middle East (e.g. Persian Gulf), and Mexico's Gulf of California coast. This clearly implies that extreme T_d events are increasing in much of the world, even if signals are more muddled in the United States. It also corroborates earlier, similar results from Im et al. (2017) and Coffel et al. (2018). Raymond et al. (2020) also found that under many carbon-emissions scenarios, T_w will regularly exceed the 35°C mark later this century in some of these regions, making human life difficult to impossible.

Finally, several of the above studies strikingly found that T_d trends had accelerated, and/or switched from negative to positive, around 1980. These included Changnon et al. (2006), Brown and DeGaetano (2013), and Freychet et al. (2020). However, not all studies confirmed this behaviour, so its global applicability is not clear.

In the present study, we continue to focus on observed long-term T_d trends in the United States. However, we exclusively examine summer (when T_d is highest and thus is most relevant to human health), use the longest reliable time interval (1948–2020), and, critically, examine trends at multiple percentiles of the summer T_d distribution, rather than just the mean and/or the annual maximum. We also introduce a simple quality-control procedure to screen out instrument errors at the extremes of T_d. In this way, we reveal a more reliable and detailed picture of long-term extreme US T_d change.

2 | METHODS

2.1 | Data selection and quality control

We use daily-maximum June–September daily T_d data from 114 ASOS (Automated Surface Observing System) stations across the continental United States. These are obtained from Iowa Environmental Mesonet (2022a) and are listed in Table S1, Supporting Information along with their locations, codes and elevations from Iowa Environmental Mesonet (2022b). These 114 stations are chosen for their relatively complete data over the 1948–2020 study period (see below), and for their spatial representativeness. June–September is used rather than the more typical June–August because many southeastern coastal stations record their highest T_d values during tropical cyclone passages, which peak in September. Relatedly, sea surface temperatures also peak in September, making it possible that coastal T_d will as well, even during fairer weather. The T_d data is supplied in integer °F, giving it a precision of ~0.5°C. We perform the quality control (below) in the native °F, but convert to °C upon processing.

Potential instrument errors affecting the extremes of T_d are screened out as follows. If a station has a daily T_d value that is noticeably higher than the rest of that station's record, then its plausibility is checked by comparison to the immediately preceding and following days, and (except in the remote western United States) to same-day readings at nearby stations. If any of these types of "neighbours" has a T_d value within less than 5°F (2.8°C) of the suspect reading, it is kept, but if all spatial and temporal "neighbours" are at least 5°F lower than the suspect reading, it is discarded and replaced with a missing value. A similar procedure is used to screen out the (much rarer) erroneously low T_d readings as well. All determinations of this type, and any exceptions to the procedure, are listed in Table S2. Proximity to a tropical cyclone (National Hurricane Center, 2022) would have also warranted keeping a high T_d reading, but this criterion was never used because all such cases turned out to be within less than 5°F of a "neighbour" anyhow, and thus none were at risk of being discarded.

For example, Memphis recorded a maximum T_d of 90°F (32.2°C) on July 8, 1996. Since (1) no other daily-maximum T_d in the Memphis record is above 84°F, (2) the previous and following days' maxima were 76 and 71°F, respectively, and (3) no nearby stations recorded extremely high T_d that day, the 90°F was deemed an instrument error and replaced with a missing value. Miami recorded a maximum T_d of 84°F (28.9°C) on both 26 and June 27, 1995, which at first also seemed erroneous, since (1) no other T_d in the Miami record is above 80°F and (2) the previous and following days' maxima were 79 and 75°F, respectively. However, nearby stations were checked and T_d as high as 83°F were found on the dates in question. Therefore, the readings in question were assumed valid and were kept. In contrast, when Miami recorded an isolated T_d of 85°F (29.4°C) on July 5, 1970, this was discarded and replaced with a missing value, as no other station in the area reported a T_d even close to 80°F that day.

More generally, some stations also have days with no maximum T_d reading at all (true missing data). This is particularly common in the early 2000s, when some years at some stations are missing 30 or more of their 122 June–September days, likely due to the above-mentioned change to Vaisala humidity sensors. Thus, after Brown and DeGaetano (2013), if a year has more than 10% of its June–September days (i.e., at least 13 days) missing and/or erroneous at a given station, that year is not used at that station. If a station has more than 10% of its 1948–2020 years (i.e., at least 8 years) unused in this manner, or unavailable to begin with, that station is not used in this study.

2.2 | Analysis

First, at each station, the aggregate climatological distribution of 1948–2020 summertime daily-maximum T_d is quantified by pooling all analysed days (up to 8906 days, if availability is complete) in one sample and taking percentiles. This allows the baseline intensity of extreme T_d to be compared and mapped across regions.

Second, at each station, each year's summertime daily-maximum T_d distribution (containing up to 122 days) is considered separately, producing year-by-year 1948–2020 time series of multiple percentiles, occasionally with a few years missing as explained above.

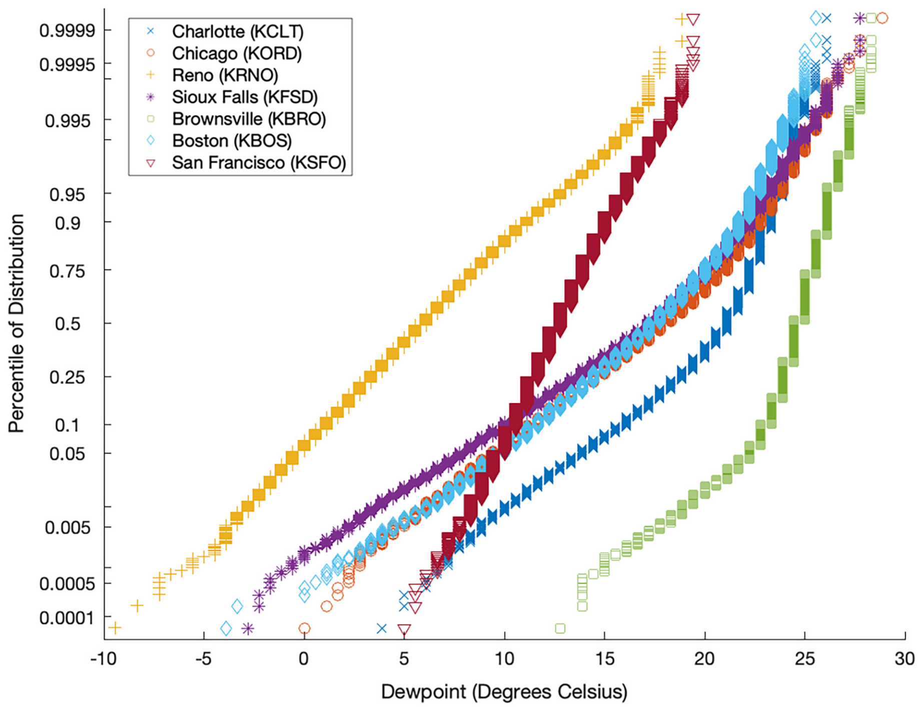

FIGURE 1 Cumulative distribution of daily-maximum T_d during June–September 1948–2020 for seven representative stations [Colour figure can be viewed at wileyonlinelibrary.com]

Due to short-term climate variability, these time series are often somewhat autocorrelated, with residual $r_1 > +0.3$ at up to 25% of stations, and >0 for the vast majority of stations. Therefore, they are analysed for trends using standard linear statistics but with the variance of the trend estimator inflated by a factor of $(1+r_1)/(1-r_1)$ when assessing significance to account for this (e.g., Santer et al., 2000; Wilks, 2019). In this way, long-term changes in different parts of the T_d distributions are quantified, and can be mapped.

Each station's trend significance is taken as a simple indicator of the strength and clarity of the local long-term trend relative to the noise; we make no formal probabilistic claim about the significance of our overall US-wide result, as that would require consideration of multiplicity (family-wise error) and field significance (e.g., Wilks, 2019). Clearly, though, far more than 5% of the stations have local trends with $p < 0.05$ (section 3.2), which would be unlikely by chance.

3 | RESULTS

3.1 | Climatological distributions

Figure 1 plots the 1948–2020 June–September daily-maximum T_d distribution at seven regionally representative stations, out of the 114 analysed. The results are largely as one would expect, with wide ranges at inland stations (e.g., Sioux Falls and Reno) but narrower ranges at some coastal and/or tropical sites (e.g., Brownsville and San Francisco). Also as expected, T_d values at the western sites (Reno and San Francisco) are much lower than those at the central and eastern sites, at least in the upper half of the distribution. This is likely due to the direction of flow around the summertime subtropical highs and gyres.

However, there are also some more surprising features in Figure 1, most notably at the very highest percentiles, where stations with otherwise quite different T_d regimes converge and/or intersect in a narrow range. In particular, the northern inland sites of Chicago and Sioux Falls, which have relatively mild T_d at most percentiles, are at least as humid as subtropical Charlotte above the 90th percentile—and almost as humid as tropical, far-southern Brownsville above the 99.9th percentile. This is likely due to intensive crop evapotranspiration under passing synoptic ridges in this heavily farmed region as discussed above (Bentley & Stallins, 2008). However, we also see this convergence for other normally contrasting site pairs where agriculture is less intensive, such as Boston/Charlotte and Reno/San Francisco. Perhaps there are strong, relatively widespread limits on extreme surface T_d due to convective instability, as found for tropical T_w by Zhang et al. (2021).

In any case, Figure 2 maps a few key T_d percentiles across all 114 of the stations, confirming the convergence at the top of the distribution (note the much narrower colour scale for the 99.9th percentile than for the 50th percentile). At the 50th percentile, that is, for "typical" daily-peak T_d, the central and eastern United States is dominated by the north–south contrast one would

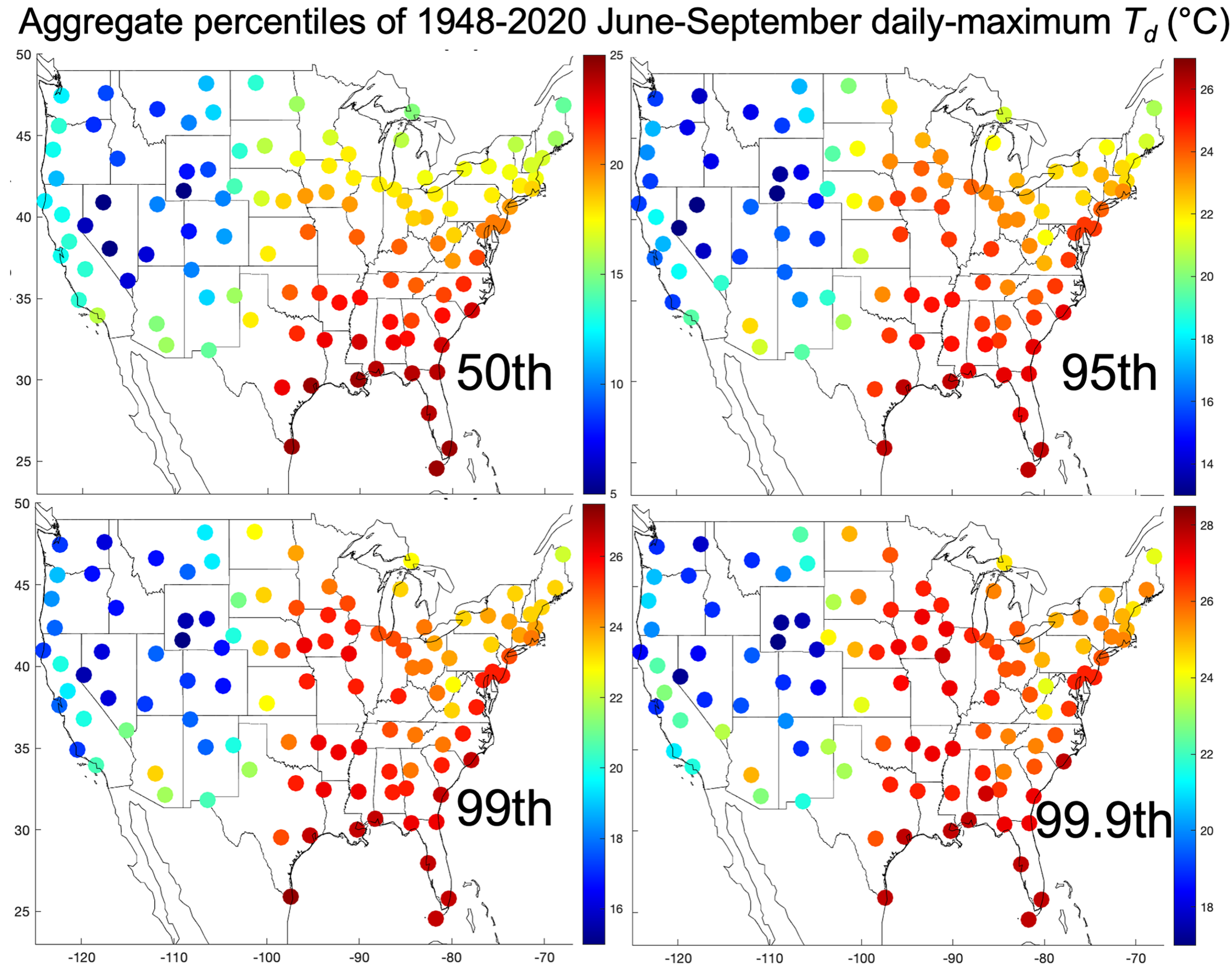

FIGURE 2 50th, 95th, 99th and 99.9th percentiles of 1948–2020 June–September daily-maximum T_d, for each station

naively expect: T_d is much higher in the Southeast and Southern Plains, close to the warm subtropical Atlantic and Gulf of Mexico, than in the Midwest or Northeast. Similarly, the dry western United States is dominated by a coastal-inland contrast, with much higher T_d west of the Sierra Nevada and Cascades (as well as in the far south owing to the North American monsoon).

However, by the 95th percentile, that is, for T_d levels that occur ~once every few weeks, much of the Midwest and coastal mid-Atlantic are as humid as the inland Southeast, and parts of the intermountain West are as humid as the coast. By the 99th (~once per summer) and 99.9th (~once per decade) percentiles, the Midwest and coastal mid-Atlantic are *more* humid than the inland Southeast, and (especially at the 99.9th) almost as humid as the coastal Southeast. Central Appalachia is much less humid than surrounding areas, including the inland Northeast to its north, at these highest percentiles. In the West, the intermountain and true-coastal T_d have largely converged at the 99.9th percentile. Instead, the warm-temperate Oregon Willamette and (especially) California Central Valleys stand out with the highest T_d, along with coastal Southern California and the monsoon region.

These patterns confirm both the general convergence at high T_d noted above, and the potential role of crop evapotranspiration in extreme T_d as found by Bentley and Stallins (2008). The most strikingly "overperforming" regions at the 99.9th percentile compared to the 50th, namely the Midwest and the Central and Willamette valleys, are intensively farmed, while "underperforming" regions like the immediate Pacific coast, Appalachia, and the inland Southeast are not. One might alternately posit that the low T_d at high percentiles in Appalachia stems from elevation, but it is unclear why this would affect median (50th percentile) T_d so much less strongly. Further, the most striking Southeastern underperformers at

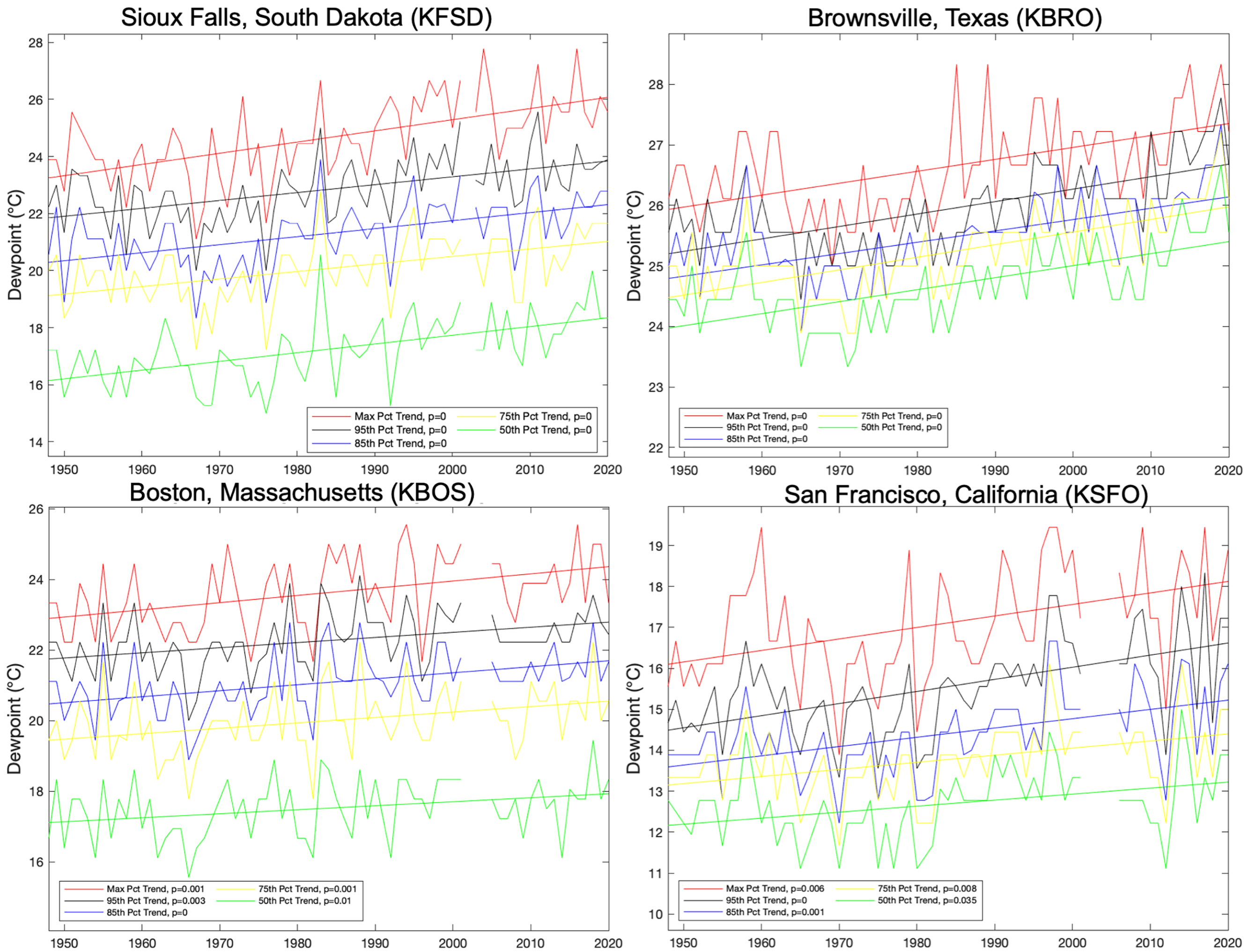

FIGURE 3 1948–2020 time series of the 50th, 75th, 85th, 95th and annual-maximum percentiles of June–September daily-maximum T_d, with linear trends and their p-values, for four representative stations

high percentiles (Knoxville, Charlotte and Atlanta) are all at lower elevations akin to Midwestern sites. In contrast, the inability of the immediate Pacific coast to reach high T_d is likely just due to the persistently low summer T there (from the cold coastal current), which sets a tight upper bound on T_d.

These aggregate T_d percentiles are likely quite reliable, because they are not sensitive to single readings which may be erroneous. Even the 99.9th percentile is only the ninth-highest daily-maximum T_d in the record at most stations, buffering it from spurious high readings (particularly after the quality control in section 3.1). Similarly, the 99th percentile is only the ~89th-highest value in the record. However, for a single summer (122 values), the 99.9th percentile is not even defined—and the 99th percentile equals the yearly maximum, which could be very sensitive to spurious readings in certain years and thus skew the trends. Therefore, in the following section we focus on trends in the 95th percentile (~sixth-highest each year) and below, which should be well buffered from errors, though we do also examine trends in the annual maximum for comparison to prior studies. The 95th percentile still shares key features with the 99th and 99.9th percentiles in Figure 2, such as the Midwestern and California Central Valley overperformance relative to the 50th percentile.

3.2 | Long-term trends

Figure 3 plots 1948–2020 time series of multiple percentiles of June–September daily-maximum T_d at four stations from Figure 1, along with fitted linear trends. Sioux Falls, Boston, Brownsville, and San Francisco are representative of the Northern Plains, the Northeast, the western Gulf coast, and California respectively. The time series are quite consistent across percentiles at each station, from the 50th percentile (median) all the way to the

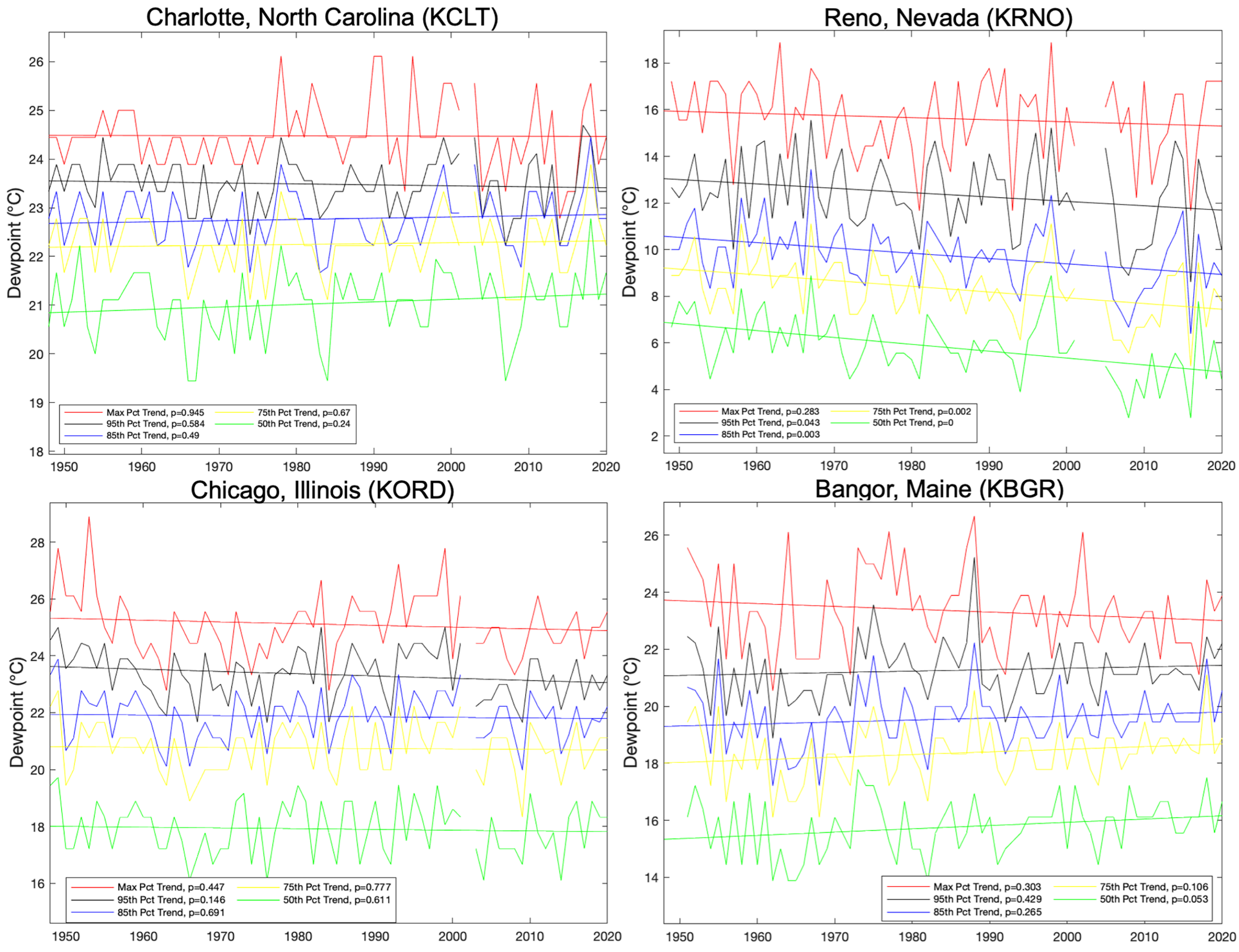

FIGURE 4 As Figure 3, for four additional stations

annual maximum. All show significant ($p < 0.05$, often <0.005) long-term increases in T_d, on the order of 1–2°C (2–4°F) total. This is greater than the global-mean T warming over the same time period, so these trends are somewhat stronger than one might expect. Sudden step changes are not apparent, so the instrumentation changes discussed by Brown and DeGaetano (2013) do not seem to have noticeable impacts (with the possible exception of Brownsville in the mid-1960s). The narrow range of both intra-annual and year-to-year T_d variability at Brownsville is again clear, reflecting the tropical, persistently humid summers at this location and causing the long-term T_d trends there in particular to be highly significant.

However, Figure 4 shows that at the remaining stations from Figure 1, the time series are quite different. At Charlotte, representing the upper Southeast, all of the T_d trends are insignificant ($p > 0.2$) and appear almost flat, with just a hint of moistening at the 50th percentile. At Reno, representing the interior West, every percentile of T_d except the maximum has in fact significantly declined ($p < 0.05$) on the order of 1–2°C since 1948, confirming the surprising results of Brown and DeGaetano (2013) and McKinnon et al. (2021). By (1), this also implies a long-term decline in q there, contrary to basic theory (e.g., Held & Soden, 2006).

Chicago appears similar to Charlotte at first glance, with insignificant ($p > 0.1$), weakly negative T_d trends at all percentiles. However, unlike at other stations, T_d seems to have suddenly dropped 0.5–1°C at the early 2000s switch to Vaisala humidity sensors. If not for this drop, the trends would likely be more positive, and indeed all surrounding stations have clearly positive T_d trends (below). Thus, Chicago may be a rare instance in which a station move or instrument change introduced an artificial trend.

Finally, at Bangor (Maine), the annual-maximum T_d has a negative trend and very high year-to-year variability, even as the other T_d percentiles all show positive trends with more modest variability. This suggests that

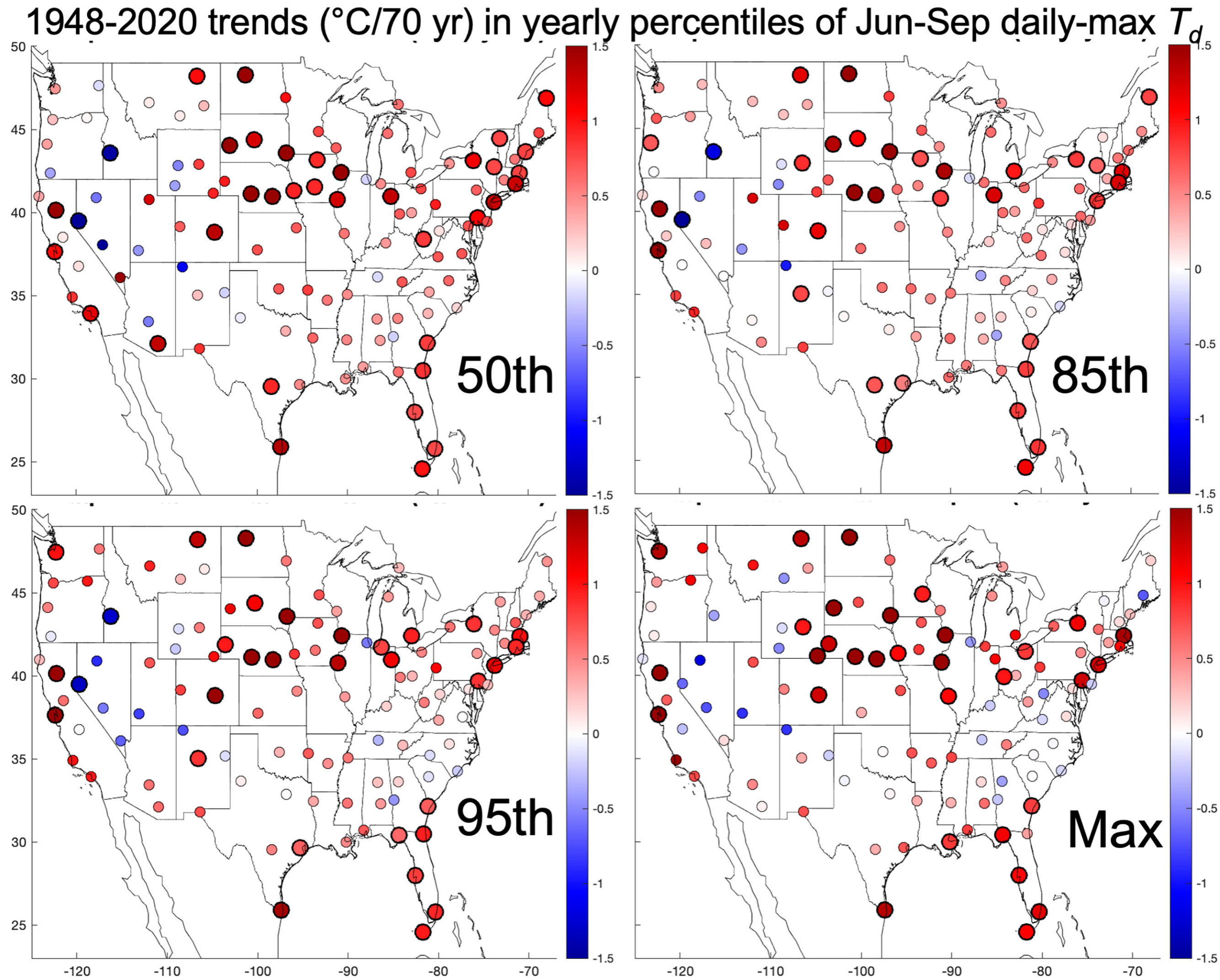

FIGURE 5 1948–2020 linear trends in the 50th, 85th, 95th and annual-maximum percentiles of June–September daily-maximum T_d, for each station. Large, bold circles denote significant ($p < 0.05$) trends

the annual-maximum T_d may not always be reliable and/or representative of most of the distribution, perhaps due to the sorts of erroneous high readings discussed in section 3.1. Reno and Sioux Falls, likewise, have much *less* negative (or more positive) trends in their annual-maximum T_d compared to other percentiles, reinforcing the idea that the maximum is not representative. Thus, by quantifying trends in high (but not annual-maximum) T_d percentiles like the 95th, we may be obtaining more broadly applicable results than previous studies did.

To generalize the above results, Figure 5 maps the 1948–2020 linear T_d trend rates across all 114 stations, for all the percentiles from Figures 3 and 4 except the 75th (omitted for conciseness). At each percentile, significant ($p < 0.05$) T_d increases of 0.5–1.5°C (70 year)$^{-1}$ are widespread in a roughly zonal swath from the Northeast across the central Midwest and into the Northern Plains, as well as in Northern California, South Texas, and Florida and vicinity, consistent with Figure 3. These increases are particularly strong in the Dakotas, Nebraska and Iowa and in Northern California, where they reach 1.5°C (70 year)$^{-1}$ or more. They are also quite strong in the coastal, urban Northeast (e.g., New York and Boston), where they reach 1.0°C (70 year)$^{-1}$ or more.

However, in a vast region spanning most of the Southeast, Southern Plains, lower Midwest, and mid-Atlantic, from Maryland to Kansas and from South Carolina to eastern New Mexico, there have been almost no long-term significant T_d trends at any percentile, with just a single exception (Charleston, West Virginia at the 50th percentile). Furthermore, in much of the Intermountain West, strong T_d *declines* on the order of 0.5–1.5°C (70 year)$^{-1}$ are widespread at each percentile, confirming McKinnon et al. (2021). These absolute drying trends are particularly strong in and near the Great Basin, though they only reach significance ($p < 0.05$) at Boise and the above-discussed Reno. In other regions, such as the far Southwest desert, the Pacific Northwest, the upper Midwest (Minnesota to Michigan), and Northern New England, T_d trends are mostly positive but inconsistent, with only a few stations and/or percentiles significant. All of this is consistent with the regional examples in Figure 4, with the exception of Chicago which again may be affected by instrumentation or siting changes given its clear dissimilarity to its neighbours in Figure 5.

There are also subtle but interesting differences between the trend patterns at different percentiles in Figure 5. Most notably, in much of the above-mentioned region of insignificant T_d trends spanning the Southeast, Southern Plains and mid-Atlantic, the summer-median (50th percentile) T_d trends are much more systematically positive than the 95th-percentile or summer-maximum T_d trends, implying a (weak) narrowing of the upper half of the T_d distribution with time. This is particularly apparent in Virginia and parts of the Carolinas, where median trends are clearly upward but high-percentile trends are as often downward as they are upward. Similar inter-percentile differences are evident in northern New England and upstate New York, where strong and significant T_d increases are clearly more widespread at the median that at the 95th percentile or maximum. However, in some other regions (e.g., parts of the Pacific Northwest), the pattern reverses, with stronger T_d increases at higher percentiles.

Finally, the pattern of trends in the annual-maximum T_d after Brown and DeGaetano (2013), shown in the last panel of Figure 5, is broadly similar to the other percentiles, with the same basic regional structure. However, several stations have opposite-signed trends in the maximum relative to all the other percentiles (as noted above for Bangor), such as Atlanta, Elkins, West Virginia, and Arcata, California. Thus, the impression is reinforced that some of the individual annual maxima at some stations could be spurious, altering the computed annual-maximum trends. In any case, the maximum trends are not always representative of trends in more frequent upper percentiles (e.g., the 85th and 95th), making them potentially less relevant, at least for day-to-day impacts.

4 | DISCUSSION

In short, long-term trends in both median and extreme summer T_d in the continental United States have a pronounced and striking spatial structure, with strong increases from the Northeast to the Northern Plains, in Florida, and in parts of California and Texas—but strong decreases in the Intermountain West (contrary to fundamental expectations on a warming planet) and largely insignificant changes elsewhere. Furthermore, in parts of the eastern United States the upper limb of the summertime T_d distribution seems to be narrowing, contrary to the more general notion that climate change increases the extremity of the weather (e.g., Seneviratne et al., 2021).

What might be causing these patterns? The contrast between the strong T_d increases in Florida and South Texas, and the much weaker, insignificant changes immediately further north, could be explained by the fact that the Gulf of Mexico has warmed (in T) significantly in summer while much of the Southeast and Central United States away from the Gulf has not, as shown in fig. 6.1 of Vose et al. (2017). This figure also indicates that the coastal Northeast has warmed dramatically in summer, which may explain the strong T_d increases there.

However, these T warming patterns still cannot explain the prominent band of very strong T_d increases across the central Midwest and Northern Plains, with much weaker T_d changes in the upper Midwest. This is because the summer T trend pattern in this region from Vose et al. (2017) is precisely the opposite, with strong warming across the upper Midwest, but very little T change (or even cooling) across the central Midwest and much of the northern Plains, where T_d has increased the most.

This dichotomy possibly suggests a role for increasing irrigation in the northern Plains, leading to T cooling and T_d moistening that advect downwind into parts of the Midwest and cause increases in heavy summer precipitation there, as outlined by DeAngelis et al. (2010) and Cook et al. (2011). The adoption of higher-yielding crop varieties over time, and resulting increase in local evapotranspiration in the Midwest, may also play a role given the importance of evapotranspiration for Midwestern T_d extremes as found by Bentley and Stallins (2008) and Kunkel et al. (1996). However, the discrepancy also may more simply stem from the much earlier 1901–1960 start period of the Vose et al. (2017) T assessment, which includes the Dust Bowl heat event of the 1930s, unlike the present study. In any case, further work is clearly needed to understand why T_d in the northern Plains and central Midwest has increased so strongly, especially in comparison to neighbouring regions that have seen little change in T_d, often despite strong warming.

The unexpected declines in T_d in the intermountain West seem to be proximately caused by declines in evapotranspiration linked to summertime soil drying, as outlined by McKinnon et al. (2021). This is quite plausible since advection of low-level humidity from outside this region is hindered by mountain ranges, allowing evapotranspiration from local soil moisture to dominate the near-surface humidity budget in summer. Declining evapotranspiration would also help explain why summers in the West have warmed so dramatically (Vose et al., 2017), by directing more energy into sensible heating of the air. However, it remains to be explained why climate models do not seem to reproduce the T_d or q declines, despite simulating the declining soil moisture and warming T (Douville et al., 2021; Lee et al., 2021).

It is also instructive to compare our results with the broader literature on United States and global T_d and T_w trends reviewed in section 1. Our trends are much stronger and more coherent than those found by Robinson (2000) for 1951–1990, confirming the importance of a long period of record to allow signal to emerge from noise. They are more similar to those found by Brown and DeGaetano (2013) for 1947–2010, especially when comparing annual-maximum trend maps. However, our examination of summertime percentiles other than the maximum (i.e., the 95th, 85th and 50th) reveals broader and clearer regions of increasing T_d than found by Brown and DeGaetano (2013), who had concluded that significant US summertime T_d increases were largely confined to the Midwest. This again suggests that the annual-maximum T_d is not representative, and/or suffers from spurious readings.

Our findings are also broadly consistent with US regional studies, such as Changnon et al. (2006) who found a recent increase in extreme Midwestern T_d events, and McKinnon et al. (2021) and Williams et al. (2014) who described the declining summer T_d in parts of the West. Interestingly, though, we find almost no sign of the sudden acceleration and/or switch from decreasing to increasing T_d around 1980, mentioned by Changnon et al. (2006), Brown and DeGaetano (2013), and (for parts of China) Freychet et al. (2020). None of the station time series in Figures 3 or 4 have such a concave-up structure, and very few of the 114 stations do in general (not shown). Some stations do show a temporary dip in T_d in the early to middle 1980s, but this does not affect longer-term trends. Thus, the acceleration finding may be regionally specific, and/or may be an artefact of using a short period of record.

Finally, to what extent might these trends impact human health, as discussed in section 2.1? Even in the most humid locations (i.e., Florida and the Midwest), the 99.9th percentile T_d values in Figure 2 are ≈28°C at most, so even a 1.5°C rise along the lines of the strongest long-term trends would not bring them above 30°C, a T_d value that humans already experience in parts of the Middle East and Asia (Freychet et al., 2020; Raymond et al., 2020). However, if these trends were to continue under several °C of additional global warming (Lee et al., 2021), extreme T_d and T_w values in humid regions of the United States could start to draw closer to 35°C, with more severe consequences.

Perhaps more concerningly, significant mortality has recently occurred during heat and humidity waves with far more modest T_d values in places where humans are unacclimated to high T_d or T_w and lack air conditioning, such as England (Adam, 2022) and coastal British Columbia (Henderson et al., 2022). Thus, in the short to medium term, the most concerning extreme T_d increases found in this study may actually be those in the inland Northeast, the Northern Plains and especially Northern California, where base extreme T_d is not as high (Figure 2) and air conditioning is less common. However, in the longer term, T_d increases in the more acclimated Gulf Coast and Midwest could become threatening as well, especially as they begin to limit outdoor work and/or bring T_w closer to the 35°C limit.

5 | CONCLUSION

In this study, we aimed to provide an up-to-date, careful, and thorough assessment of the pattern of extreme summertime dewpoints (T_d) in the United States, and of long-term T_d trends in the context of global warming, given the threat that high T_d potentially poses to human health and survival. We found that while typical June–September T_d values follow the expected north–south and east–west contrasts, extreme T_d percentiles have a more complex pattern, with strong overperformance in heavily farmed regions like the Midwest and California Central Valley and underperformance in parts of the inland Southeast, Appalachia and the immediate Pacific coast. For long-term (1948–2020) T_d trends, we found a common, striking pattern across all examined percentiles, with strong increases from the Northeast to the Northern Plains and in Florida, south Texas, and northern California, but only weak changes elsewhere and clear *declines* in the intermountain West, contrary to basic expectations under climate change but in agreement with several recent studies. Median T_d has also increased much more systematically than upper-percentile T_d in parts of the eastern United States, suggesting an unexplained narrowing of the local T_d distributions with time.

This was a limited, focused study of observed T_d and its trends, which have received less attention than T trends in the climate-change literature. Future work, however, should combine hourly T_d and T data to understand the controls on extreme T_w and its trends, and should also more deeply examine the reasons for the diverging patterns in T_d trends found in this study.

Similar analyses at the global scale would also be of interest, as would a systematic comparison between observed T_d trends and those simulated by climate model ensembles. All of these avenues would further improve our understanding of the risk from increasing extreme humidity, and are promising candidates for future studies.

AUTHOR CONTRIBUTIONS

Jacob Scheff: Conceptualization; methodology; writing – original draft; resources; supervision; investigation; writing – review and editing; formal analysis; software. **James Cody Burroughs:** Conceptualization; methodology; software; investigation; validation; formal analysis; visualization.

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ORCID

Jacob Scheff https://orcid.org/0000-0003-1294-3447

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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