Nonlinear increases in extreme temperatures paradoxically dampen increases in extreme humid-heat

Ethan D Coffel1,2, Radley M Horton1, Jonathan M Winter1,3 and Justin S Mankin1,4,5

1 Neukom Institute, Dartmouth College, United States of America
2 Department of Geography, Dartmouth College, United States of America
3 Department of Earth Sciences, Dartmouth College, United States of America
4 Lamont-Doherty Earth Observatory of Columbia University, United States of America
E-mail: ecoffel@dartmouth.edu

Keywords: climate change, extreme heat, humidity, land-atmosphere coupling

Abstract
Nonlinear increases in warm season temperatures are projected for many regions, a phenomenon we show to be associated with relative surface drying. However, negative human health impacts are physiologically linked to combinations of high temperatures and high humidity. Since the amplified warming and drying are concurrent, the net effect on humid-heat, as measured by the wet bulb temperature ($T_W$), is uncertain. We demonstrate that globally, on the hottest days of the year, the positive effect of amplified warming on $T_W$ is counterbalanced by a larger negative effect resulting from drying. As a result, the largest increases in $T_W$ and $T_x$ do not occur on the same days. Compared to a world with linear temperature change, the drying associated with nonlinear warming dampens mid-latitude $T_W$ increases by up to 0.5 °C, and also dampens the rise in frequency of dangerous humid-heat ($T_W > 27$ °C) by up to 5 d per year in parts of North America and Europe. Our results highlight the opposing interactions among temperature and humidity changes and their effects on $T_W$, and point to the importance of constraining uncertainty in hydrological and warm season humidity changes to best position the management of future humid-heat risks.

Introduction
Humid-heat extremes pose a severe risk to human health [1, 2], and temperature extremes more broadly can reduce economic performance [3, 4], damage crops and ecosystems [5–7], and harm infrastructure [8–10]. Climate change is increasing global mean temperature by altering the surface radiative balance, raising the chances of extreme heat events across the world [11–14]. At regional scales, land-atmosphere interactions among soil moisture and vegetation control the partitioning of energy into sensible and latent heat fluxes, playing a significant role in controlling extreme temperatures, drought, and heat wave statistics in the observational record and in climate models [15–22]. Further, recent research has identified soil drying and associated changes in surface energy partitioning to be a crucial driver of nonlinear temperature changes relative to the warm season mean [23]. In some regions, climate models project that extreme temperatures will increase an additional 1 °C–2 °C beyond warm season mean temperatures—indicating that mean changes alone cannot account for changes in the tails. This amplified warming of temperature extremes has been linked to declines in the fraction of total surface energy fluxes from latent heat, so that in regions where the surface is projected to dry, temperatures are projected to warm more rapidly as more energy is partitioned to sensible heating of the air [23].

While high temperatures have diverse and serious impacts on economies and ecosystems, human health is most tightly linked to the physiological consequences of extreme humid-heat [1]. Constraining uncertainty in the response of humid-heat to climate warming is an urgent task, as recent research has suggested that a critical threshold for human humid-heat tolerance could be approached or exceeded in parts of the world during the 21st century [24–28]. This
threshold is defined using the wet bulb temperature \( T_W \), the saturation temperature of an air parcel. When \( T_W \) exceeds the human skin temperature, approximately 35 °C, evaporative cooling is no longer effective as a means of shedding body heat. Prolonged exposure to such conditions causes heat illness and eventually death [29]. In addition, much lower \( T_W \) values between 27 °C and 32 °C have routinely caused tens of thousands of deaths and serious heat-related illnesses in recent decades [2], particularly among the world’s most vulnerable populations. Uncertainty of a few degrees Celsius at the warm tail of the \( T_W \) distribution is therefore essential to constrain, as the mortality risks it poses to people are considerable.

Recent research has shown that anomalously high specific humidity, rather than temperature, is often the dominant driver of present-day extreme humid-heat events [30], while a dry land surface often accompanies the extreme temperature events projected in climate models [31, 32]. Because \( T_W \) is nonlinearly dependent on both temperature and humidity, it is not evident how the competing effects of temperature (and its associated surface drying) will combine with specific humidity to alter future risks of extreme humid-heat. Simultaneous changes in these quantities complicate estimates of the \( T_W \) response, as temperature and specific humidity not only influence \( T_W \) individually, but are also themselves interactive, responding in opposite directions to surface drying (temperature increases more, specific humidity increases less). These direct and indirect effects of temperature and humidity on \( T_W \) suggest that surface drying could either increase or decrease humid-heat, depending on the balance of the two changes.

We use daily maximum temperature \( T_{\text{max}} \) amplification, the nonlinear change in temperature that results in the top half of the \( T_{\text{max}} \) distribution warming more than the warm season average (or median) \( T_{\text{max}} \), which appear to be driven largely by land-atmosphere interactions, to assess whether they lead to nonlinear \( T_W \) changes in a suite of global climate models. We investigate the relationships between \( T_{\text{max}} \) amplification and its associated specific humidity change in the context of land-surface drying, and demonstrate the dependence of the magnitude and frequency of extreme \( T_W \) on each at global and regional scales. We then illustrate how \( T_{\text{max}} \) amplification-driven changes in \( T_W \) affect the frequency of and population exposure to humid-heat extremes.

### Data and methods

We utilize climate projections from a suite of 16 global climate models (GCMs) from the Coupled Model Intercomparison Project Phase 5 (CMIP5) [33]. All models that provide the requisite variables for computing daily \( T_W \) (daily maximum temperature (Tmax), specific humidity (Huss), and sea level pressure (PsL)), as well as daily sensible (Hfss) and latent heat fluxes (HFs), are used (supplementary material table 1). Sea level pressure is used as opposed to true surface pressure due to its greater availability in the CMIP5 ensemble; the difference in pressure is found to have a less than 0.2 °C effect on global \( T_W \) estimates, and a still smaller effect for \( T_W \) extremes which occur almost exclusively in regions near sea-level. All model projections are made in the period 2061–2085 and are compared with historical simulations spanning 1981–2005. The Representative Concentration Pathway (RCP) 8.5 [34] emissions scenario is used to maximize the climate change signal. All model data are regridded using a linear interpolation procedure to a \( 2^\circ \times 2^\circ \) resolution to facilitate inter-model spatial comparison. This resolution is generally in the middle of the native CMIP5 model resolutions (see table 1)
and ensures that the models are not all being unphysically downscaled. All analysis is conducted on the locally-defined warm season, estimated for each model and each grid cell as all unique months in which the annual maximum air temperature (TXₙ) has occurred during the historical period. The regridding procedure has minimal effect on the model-estimated timing of the warm season (see supplementary material figure S1, which is available online at stacks.iop.org/ERL/14/084003/mmedia).

Daily Tₑ is calculated between 60 °S and 60 °N using the algorithm presented in Davies-Jones, 2008 [35], implemented in HumanIndexMod [36], and ported to Matlab [37]. Estimating Tₑ at the time of maximum air temperature rather than the true daily maximum Tₑ creates a negligible downward bias in Tₑ [24].

Changes in Tₑ and Tₑ decile thresholds are calculated for each grid cell and for each model. The resulting changes are averaged over all land grid cells between 60 °S and 60 °N. Tₑ amplification is calculated for different percentiles. For example, Tₑ amplification on the TXₙ (annual maximum daily temperature) day is calculated for each model and each grid cell as the projected change in TXₙ (averaged across all years) minus the projected change in the warm season 50th percentile Tₑ (also averaged across all years). We denote this amplification using the following notation:

$$\Delta TXₑ - \Delta Tₑ^{50},$$

where \(\Delta TXₑ\) is the average change in TXₑ (i.e. 100th percentile of the annual Tₑ distribution) and \(\Delta Tₑ^{50}\) is the average change in the 50th percentile of the Tₑ distribution. Tₑ amplification on the Tₑₙ day is calculated similarly as the change in the annual maximum Tₑ minus the change in the warm season 50th percentile daily maximum Tₑ. We similarly denote this amplification as:

$$\Delta Tₑₙ - \Delta Tₑ^{50}.$$

We note that our results are robust to the choice of defining amplification (\(\Delta TXₑ - \Delta Tₑ^{50}\) or \(\Delta Tₑₙ - \Delta Tₑ^{50}\)) as relative to the warm season 50th percentile or to the warm season mean.

Tₑ amplification on the Tₑₙ day is calculated as the projected change in Tₑ on the day of the annual maximum Tₑ minus the projected change in warm season 50th percentile Tₑ. We denote this amplification as:

$$\Delta (Tₑ|Tₑₙ) - \Delta Tₑ^{50}.$$

Similarly, Tₑ amplification on the TXₑ day is calculated as the projected change in Tₑ on the TXₑ day minus the projected change in the warm season 50th percentile Tₑ, denoted as:

$$\Delta (Tₑ|TXₑ) - \Delta Tₑ^{50}.$$

Tₑ amplification across the Tₑ distribution is calculated as the mean projected change in Tₑ on all days in each warm season Tₑ percentile \(Tₑ^{D}\) where \(D\) is the decile in which the calculation is being performed) minus the warm season 50th percentile change in Tₑ:

$$\Delta (Tₑ|Tₑ^{D}) - \Delta Tₑ^{50}.$$

Similarly, Tₑₙ amplification across the Tₑ distribution is calculated as the mean projected change in Tₑ on all days in each warm season Tₑₙ percentile minus the warm season 50th percentile change in Tₑₙ:

$$\Delta (Tₑₙ|Tₑ^{D}) - \Delta Tₑ^{50}.$$

We also assess specific humidity (Huss) and evaporative fraction (EF) amplification across the Tₑ and Tₑₙ distributions. The EF is the ratio of the latent heat flux to the total heat flux, defined as:

$$EF = \frac{Qₑ}{Qₑ + Q_H},$$

where \(Qₑ\) is the latent heat flux, and \(Q_H\) is the sensible heat flux. As above, we denote these specific humidity and EF amplifications as:

The specific humidity amplification across the Tₑ distribution:

$$\Delta (\text{Huss}|Tₑ^{D}) - \Delta (\text{Huss}|Tₑ^{50}).$$

The specific humidity amplification across the Tₑₙ distribution:

$$\Delta (\text{Huss}|Tₑₙ^{D}) - \Delta (\text{Huss}|Tₑₙ^{50}).$$

The EF amplification across the Tₑ distribution:

$$\Delta (\text{EF}|Tₑ^{D}) - \Delta (\text{EF}|Tₑ^{50}).$$

The EF amplification across the Tₑₙ distribution:

$$\Delta (\text{EF}|Tₑₙ^{D}) - \Delta (\text{EF}|Tₑₙ^{50}).$$

To estimate the effect of Tₑ amplification’s temperature component on Tₑ, for each model and for each grid cell, we calculate the Tₑ change on days in each decile of the Tₑ distribution using the decile’s projected Tₑ change and the specific humidity change at the Tₑ median. To estimate the effect of Tₑ amplification’s specific humidity component on Tₑ, we repeat the calculation using each Tₑ decile’s projected specific humidity change and median Tₑ change. The total effect of Tₑ amplification on Tₑ change is estimated by repeating the calculation for each Tₑ decile’s projected specific humidity change and each decile’s projected Tₑ change. The components of Tₑ change due to temperature and specific humidity change are calculated by subtracting the median Tₑ change from the mean of the Tₑ change across the top five Tₑ deciles.

The number of days per warm season that exceed Tₑ thresholds is estimated using our calculations of Tₑ amplification-driven changes in Tₑ. Model bias in absolute Tₑ is removed via a percentile-matching procedure using the ERA-Interim reanalysis. For each selected Tₑ threshold, the corresponding Tₑ percentile is found for each grid cell in ERA-Interim Tₑ data. The number of days per warm season that exceed this Tₑ percentile is then calculated for each model and
Results and discussion

We define an amplification to be the projected change in $T_{x}$, $T_{w}$, or other climate variables at a particular point in the distribution relative to the projected change in that variable at the 50th percentile across the local warm season. Positive (negative) amplification is when the magnitude of the local warm season change in percentiles above the 50th percentile is greater (less) than the magnitude of change at the 50th percentile. Positive (negative) amplification implies that there is not simply a mean shift in the distribution, but also an increase (decrease) in the variance of the right tail.

Global-scale nonlinear increases in warm temperatures are apparent by 2061–2085 across the 16 CMIP5 models forced with RCP 8.5 (see Methods). $T_{x}$ changes are negatively amplified for percentiles below the local warm season’s 50th $T_{x}$ percentile and positively amplified for percentiles above it (figure 1(a)). In contrast, warm season $T_{w}$ changes show less variation across the $T_{w}$ distribution, suggesting a mean shift in response to forcing. The multi-model median globally-averaged $T_{x}$ amplification on the $T_{x}$ day (the 100th $T_{x}$ percentile in each year; $\Delta T_{x} - \Delta T_{x50}$) is 0.34 °C, bringing the total $T_{x}$ change to over 4.5 °C, but shows wide spatial variation, with parts of the eastern and southwestern US, northern Europe, and China exhibiting well over a degree of amplification (figure 1(b)). This positively-amplified warming of high $T_{x}$ values at both global and regional scales has been linked to land-atmosphere coupling and land surface drying [23], which allows energy to be preferentially partitioned into sensible rather than latent heat flux. $T_{w}$, despite having temperature as a contributing factor (along with humidity and atmospheric pressure), exhibits less amplification than $T_{x}$ across the globally-averaged distribution: the multi-model median annual maximum $T_{w}$ day (the 100th $T_{w}$ percentile in each year; $\Delta T_{w} - \Delta T_{w50}$) rises 0.24 °C more than the warm season 50th percentile $T_{w}$ (figure 1(c)). Parts of North Africa and the Middle East have amplified $T_{w}$ of just under a degree Celsius, though the magnitudes and ubiquity of $T_{w}$ amplification (figure 1(c)) is less than that for $T_{x}$ amplification (figure 1(b)).

As global temperatures rise, the multi-model median projects that $T_{x}$ on the $T_{w}$ day ($\Delta T_{x} \mid T_{w}$) and $T_{w}$ on the $T_{x}$ day ($\Delta T_{w} \mid T_{x}$) will increase by 3 °C–6 °C and 2 °C–4 °C, respectively, as both heat and humidity intensify for the most extreme temperatures (figures 2(a), (b)). Because $T_{x}$ influences $T_{w}$, changes in both variables interact across their distributions. For example, $T_{x}$ and $T_{w}$ are negatively amplified on the $T_{w}$ and $T_{x}$ days, respectively, robustly showing less to no warming ($-1$ °C to $-0.5$ °C) as compared with their respective seasonal 50th percentile changes in parts of the subtropics and mid-latitudes (figures 2(c), (d)). This means that on the future days that have the year’s hottest temperatures, the increase in humid-heat intensity is projected to be less than the median increase across the warm season. Thus the nonlinear increase in $T_{x}$ does not appear drive a nonlinear increase in $T_{w}$. Globally, this interactive negative amplification occurs across the top quartile of both the $T_{x}$ and $T_{w}$ distributions (figures 2(e), (f)).

Our above analysis highlights that conditions associated with $T_{x}$ amplification dampen increases in $T_{w}$ on days at high $T_{x}$ percentiles (figures 2(d), (f)), while conditions associated with $T_{w}$ amplification dampen increases in $T_{x}$ on days at high $T_{w}$ percentiles (figures 2(c), (e)). These results suggest that nonlinear increases in extreme temperatures alone are insufficient to cause nonlinear increases in humid-heat extremes. We explore this result by demonstrating how interactions between $T_{x}$ and $T_{w}$ are mediated by changes in the evaporative fraction (EF), defined as the ratio of the latent heat flux to the total heat flux, and specific humidity. Prior work has linked $T_{x}$ amplification to land surface drying and associated declines in EF [23]. We confirm this result, showing that EF has a more negative change (drying) on days above the 50th $T_{x}$ percentile, and a more positive change on days below it (figures 3(a); S2(a)). In addition, relative EF change across the $T_{w}$ distribution is generally more positive on days above the 50th $T_{w}$ percentile (figures 3(b); S2(b)). Together, these results suggest...
that the highest $T_x$ days will become relatively drier while the highest $T_W$ days will become relatively wetter, and highlight the fact that the hottest days often are not the same as those with the highest $T_W$ values [30].

Specific humidity responds directly to warming due to the ability of warmer air to hold more moisture. At the same time, however, humidity is shaped by the surface drying that is tightly associated with $T_x$ amplification. Concurrent with the relative changes in EF across the $T_x$ and $T_W$ distributions described above are corresponding changes in specific humidity: when EF change is more positive, specific humidity change is also more positive, a direct result of increased moisture available for evaporation. Accordingly, across the $T_x$ distribution, specific humidity change is more negative on days above the 50th $T_x$ percentile and more positive on days below it (figure 3(c)). In contrast, across the $T_W$ distribution, specific humidity change is more positive on days above the 50th $T_W$ percentile and more negative on days below it (figure 3(d)). Thus within the confines of local land-atmosphere coupling, the linkages between $T_x$ amplification and $T_W$ change center around land surface drying, as indicated by declines in EF. As the surface dries, EF declines, energy is preferentially partitioned to sensible rather than latent heat flux, and temperatures rise more. At the same time, the lack of surface moisture for evaporation dampens the increase in specific humidity, creating a drier but hotter environment on days in the top half of the $T_x$ distribution. The opposite effect occurs on days in the top half of the $T_W$ distribution.

Figure 4 shows the total effect of $T_x$ amplification on $T_W$ change on days above the 50th $T_x$ percentile relative to $T_W$ change at the 50th $T_x$ percentile, encompassing the combined effects of temperature and humidity. There is model agreement on the negative amplification of $T_W$ change associated with $T_x$ amplification in North America, Europe, and Central Asia, regions where the specific humidity component of $T_x$ amplification is projected to strongly dampen $T_W$ (figure S5(b)), and its temperature component is projected to have weak effects on $T_W$ (figure S5(a)). Here, $T_W$ increases are projected to be less than they would be in a world with only linear temperature and specific humidity changes. In much of the rest of the world, there is not model agreement on the direction of $T_W$ change associated with $T_x$ amplification. In these regions, the generally positive effect of the temperature component and the negative effect of the specific humidity component on $T_W$ balance out, making the magnitude of $T_W$ amplification small and its sign uncertain. However, the individual effects of the temperature and specific humidity components of $T_x$ amplification on $T_W$ change are large, meaning that small differences in either component could strongly affect $T_W$ change (figure S5).

Because $T_x$ amplification can contribute to the magnitude of $T_W$ increases in some regions, we seek to clarify the implications of $T_x$ amplification-induced $T_W$ changes on people. We do this by examining how
$T_x$ amplification contributes to changes in the frequency of $T_w$ days above critical wet bulb thresholds. $T_w$ proxies the effectiveness of evaporative cooling for people, and global mean climate warming will increase the frequency of extreme humid-heat events everywhere. The number of days with a $T_w$ above 27 °C, a level above which mortality is observed to rise in cities across the United States (figure S6), is projected to increase by 5–50 or more days per year in much of the tropics and mid-latitudes, irrespective of $T_x$ amplification (figure 5(a)). Such a response causes increases in global population exposure to $T_w$ thresholds from 27 °C to 31 °C of 25 to 150 billion person days per year, respectively (figure 5(b)) under a scenario of population growth consistent with RCP 8.5 (see Data and methods).

The $T_w$ change due to $T_x$ amplification generally reduces the occurrence of extreme humid-heat events above a $T_w$ of 27 °C in eastern North America and Europe (−2 to −4 d per year) and has little effect on their occurrence in the tropics (figure 5(c)). These reductions in occurrence as compared to a world with linear temperature and specific humidity change make a substantial contribution (−10 to −50%; figure S7) to the overall changes in the frequency of humid-heat extremes in Europe and eastern North America shown in figure 5(a). Because most of the highest $T_w$ values occur in the tropics where $T_x$ amplification has uncertain and near zero effect on $T_w$ change, the globally-averaged effect of $T_x$ amplification is to slightly reduce the number of extreme $T_w$ days exceeding thresholds ranging from 27 °C to 31 °C by 0.1 to 1 day per year, respectively (figure 5(d)). Additionally, because many of the regions where the effect of $T_x$ amplification on $T_w$ change is uncertain are also densely populated, $T_x$ amplification is projected to result in −3 to +2.5 billion more annual person-days per year of exposure to $T_w$ values above 27 °C.

Figure 2. Interactions between $T_x$ and $T_w$ change. (a) Multi-model median projected change in $T_x$ on the $T_{w50}$ day ($\Delta(T_x|T_{w50})$), (b) Multi-model median projected change in $T_w$ on the $TX_x$ day ($\Delta(T_w|TX_x)$), (c) $T_x$ amplification on the $T_{w50}$ day, defined as the multi-model median projected change in $T_w$ on the $T_{w50}$ day minus the projected change in warm season 50th percentile $T_w$ ($\Delta(T_x|T_{w50})$ − $\Delta(T_w|T_{w50})$). (d) $T_w$ amplification on the $TX_x$ day, defined as the multi-model median projected change in $T_w$ on the $TX_x$ day minus the projected change in warm season 50th percentile $T_w$ ($\Delta(T_w|TX_x)$ − $\Delta(T_w|T_{w50})$). Hatching in (c) and (d) indicates less than 2/3 model agreement on the sign of the amplification. (e) Multi-model median global mean $T_x$ amplification across the $T_w$ distribution ($\Delta(T_x|T_{w50})$). Hatching in (c) and (d) indicates less than 2/3 model agreement on the sign of the amplification. (f) Multi-model median global mean $T_w$ amplification across the $T_x$ distribution. Boxplots show the 10th–90th percentile range across the model ensemble.
Discussion and conclusions

Our results show that in the global mean, nonlinear $T_x$ increases are counterbalanced by the dampened increases in specific humidity associated with $T_x$ amplification, resulting in near-linear changes in the $T_W$ distribution (figures 3(a), 3(c), (d)). This global-scale linearity, however, belies important variations in $T_x$-amplified $T_W$ changes at the regional scale: $T_x$ amplification generally dampens the warm season mean $T_W$ increase in mid-latitudes where warm season moisture is limited (figure 4), and has little or uncertain effect on $T_W$ change in the tropics. This response of $T_W$ is tightly coupled to the specific humidity change that is projected on hot days (figure 3(c)). Globally averaged, $T_x$ amplification serves to slightly reduce the frequency of extreme $T_W$ values of 27 °C or higher as compared to a world with only linear temperature and specific humidity change, a result dominated by eastern North America and Europe where robust warm season mean drying is projected. Because models suggest that declines in surface moisture (proxied by the evaporative fraction) are associated with amplified warming of the hottest temperatures, our results show that more warming of hot extremes can paradoxically reduce the occurrence of humid-heat extremes in some mid-latitude regions.

Land-atmosphere feedbacks play a role in controlling temperature extremes [23, 40], and our results demonstrate that such feedbacks also exert an important influence over the change in $T_W$ extremes. On extreme $T_W$ days, specific humidity is the primary driver of $T_W$ change, while temperature is the primary driver of $T_W$ change on extreme $T_x$ days (figure S8). Accordingly, within the context of land-atmosphere feedbacks, the extent to which $T_x$ amplification modifies extreme $T_W$ change largely depends on how strongly specific humidity responds to surface drying. At the same time, we note that recent work [41] has detailed the importance of atmospheric dynamics and moisture advection in controlling continental humidity; such processes will also influence the changes in humid-heat.

These results emphasize the need for more research investigating the interactions among precipitation, soil moisture, vegetation, and surface heat fluxes, along with their representations in climate models [22]. In particular, the most extreme $T_W$ events often occur along coastlines, making the model parameterizations of sub-grid scale and coastal processes of particular interest. Future increases in model resolution may enable study of these coastal regions with strong temperature and humidity gradients. In this work, we focus on the thermodynamic drivers of nonlinear temperature and $T_W$ change. However, changes in atmospheric circulation patterns have been shown to influence the occurrence frequency of extreme temperature events in the historical record [42], and it is likely that dynamical changes may influence $T_W$ extremes as well.

We have estimated this relationship between $T_x$ amplification and its associated specific humidity
change in 16 global climate models and four climate regions, but the extent to which $T_s$ changes vary within and across simulations may have a substantial effect on $T_W$ change. There is evidence that models may misrepresent the strength of land-atmosphere coupling in some contexts [32], and thus also misrepresent the relationships among evaporative fraction, temperature, and specific humidity that drive $T_s$ amplification. Further, because of the dynamical processes that determine moisture advection from the ocean to the land, uncertainty in both ensemble and model representations of internal variability and surface processes will shape uncertainty in how humid such heat extremes become. Because $T_s$ amplification generally has a negative influence on $T_W$, an overestimation of the strength of this amplification could result in real-world $T_W$ values increasing more than projected.

Such structural and dynamical uncertainties, however, are crucial to preserve in the diagnosis of the risks posed by humid-heat events. While the magnitude of projected extreme $T_W$ increases across the CMIP5 model ensemble are smaller than for $T_s$ due to the countervailing effects of temperature and humidity change [43], human physiology and health is far more sensitive to small changes in the tails of $T_W$ than in temperature alone. This suggests that small uncertainties in $T_W$ projections can translate into large uncertainties in the risks of health impacts from humid-heat extremes. Accordingly, it is important that impacts-focused research recognize and present the wide range of projected extreme heat and humid-heat outcomes to best position effective climate risk management [44]. It is equally important to consider the spatial heterogeneity of extreme humid-heat and human mortality across the world. In the United States, where air conditioning is widely accessible and most people do not work outdoors, daily mortality begins to sharply increase above $T_W$ values of approximately 27°C (figure S6). While there may be variation in the mortality response to humid-heat in regions in the tropics and subtropics that regularly experience heat stress, human tolerance to high $T_W$ values is constrained by physiology [1, 29]. Additionally, in regions where baseline health is lower, air conditioning is more expensive or unavailable, and a higher fraction of people perform outdoor physical labor, mortality could respond more sharply to humid-heat than in the US. A more detailed understanding of the regional variation in mortality responses to humid-heat is constrained by health data availability. Given the potential for $T_W$ values to approach the theoretical limits of human tolerance (35°C), more research is urgently needed to bound the health risks posed by frequent, unprecedented humid-heat in densely populated parts of the world.

Acknowledgments

We acknowledge the World Climate Research Programme’s Working Group on Coupled Modelling, which is responsible for CMIP, and we thank the climate modeling groups for producing and making available their model output. For CMIP the US Department of Energy’s Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals.

Funding

Funding for this work was provided by the Dartmouth Neukom Institute and NSF Award OIA 1556770.

Author contributions

E D C, J S M, R M H, and J M W conceived of the study. E D C and J S M designed the analysis. E D C performed the analysis. E D C, J S M, R M H, and J M
W interpreted the results. E D C and J S M wrote the manuscript with contributions from R M H and J M W.

Competing interests

The authors have no competing interests.

Data and materials availability

Raw CMIP5 data is freely available from the Earth System Research Grid. Intermediate data and processing software is available at www.ethancoffel.com/data/nonlinearT.

ORCID iDs

Ethan D Coffel @ https://orcid.org/0000-0003-3172-467X
Radley M Horton @ https://orcid.org/0000-0002-5574-9962
Jonathan M Winter @ https://orcid.org/0000-0003-1261-4774

References

[1] Coffel E D et al 2018 The science of adaptation to extreme heat Resilience—The Science of Adaptation to Climate Change ed T Frank and Z Zommers (Amsterdam: Elsevier)
[2] Glaser J et al 2016 Climate change and the emergent epidemic of CKD from heat stress in rural communities: the case for heat stress nephropathy Clin. J. Am. Soc. Nephrol. 11 1472–83
[3] Moore F C and Diaz D B 2015 Temperature impacts on economic growth warrant stringent mitigation policy Nat. Clim. Change 5 127–31
[4] Burke M, Hsiang S M and Miguel E 2015 Global nonlinear effect of temperature on economic production Nature 527 235–9
[5] Lesk C, Coffel E, D’Amato A W, Dodds K and Horton R 2017 Threats to North American forests from southern pine beetle with warming winters Nat. Clim. Change 7 7713–7
[6] Lesk C, Rowhani P and Ramankutty N 2016 Influence of extreme weather disasters on global crop production Nature 529 64–7
[7] Schlenker W and Roberts M J 2009 Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change Proc. Natl Acad. Sci. 106 15394–8
[8] Coffel E D, Thompson T R and Horton R M 2017 The impacts of rising temperatures on aircraft takeoff performance Clim. Change 144 381–8

Figure 5. The influence of $T_x$ amplification on the frequency of extreme humid-heat events. (a), (c) Multi-model median additional number of days per year with a $T_W$ exceeding 27 °C due to the (a) all $T_W$ warming under RCP 8.5 and (c) the estimated $T_x$ amplification-driven $T_W$ change (the result shown in figure 4). Hatching indicates less than 2/3 model agreement on the direction of change. (b), (d) Globally averaged additional number of days per year exceeding $T_W$ thresholds from 27 °C–31 °C due to (b) all $T_W$ warming under RCP 8.5 and (d) the estimated $T_x$ amplification-driven $T_W$ change (red), and the projected change in the number of person-days per year of population exposure to these $T_W$ thresholds (black). Boxplots show the 10th–90th percentile range across the model ensemble.
[9] Coffel E and Horton R 2015 Climate change and the impact of extreme temperatures on aviation Weather. Clim. Soc. 7 94–102
[10] Auffhammer M, Baylis P and Hausman C H 2017 Climate change is projected to have severe impacts on the frequency and intensity of peak electricity demand across the United States Proc. Natl. Acad. Sci. USA 114 1886–91
[11] Horton R M, Mankin J S, Lesk C, Coffel E and Raymond C 2016 A review of recent advances in research on extreme heat eventsCurr. Clim. Change Rep. 2 242–59
[12] Horton R M, Coffel E D, Winter J M and Bader D A 2015 Projected changes in extreme temperature events based on the NARCCAP model suite Geophys. Res. Lett. 42 7722–31
[13] Rahmstorf S and Coumou D 2012 Increase of extreme events in a warming world Proc. Natl. Acad. Sci. 109 4708–4708
[14] Meehl G A and Tebaldi C 2004 More intense, more frequent, and longer lasting heat waves in the 21st century Science 305 994–7
[15] Miralles D G, Teuling A J, van Heerwaarden C C and Vila-Guerau de Arellano J 2014 Mega-heatwave temperatures due to combined soil desiccation and atmospheric heat accumulation Nat. Geosci. 7 343–9
[16] Hirschi M et al 2011 Observational evidence for soil–moisture impact on hot extremes in southeastern Europe Nat. Geosci. 4 17–21
[17] Zampieri M et al 2009 Hot European summers and the role of soil moisture in the propagation of mediterranean drought J. Clim. 22 4747–58
[18] Seneviratne S I et al 2010 Investigating soil moisture–climate interactions in a changing climate: a review Earth-Sci. Rev. 99 125–61
[19] Skinner C, Poulsen C J and Mankin J S 2018 Amplification of heat extremes by plant CO2 physiological forcing Nat. Commun. 9 1–11
[20] Mueller N D et al 2016 Cooling of US Midwest summer temperature extremes from cropland intensification Nat. Clim. Change 6 317–22
[21] Mankin J S, Smerdon J E, Cook B I, Williams A P and Seager R :10.1175/JCLI-D-17-0213.1 2017 The curious case of projected 21st-century drying but greening in the American West J. Clim. 30 869–710
[22] Mankin J S et al 2018 Blue water trade-offs with vegetation in a CO2-enriched climate Geophys. Res. Lett. 45 3115–25
[23] Donat M G, Pitman A J and Seneviratne S I 2017 Regional warming of hot extremes accelerated by surface energy fluxes Geophys. Res. Lett. 44 7011–9
[24] Coffel E D, Horton R M and De Sherbinin A 2018 Temperature and humidity based projections of a rapid rise in global heat stress exposure during the 21st century Environ. Res. Lett. 13 014001
[25] Pal J S and Eltahir E A B 2015 Future temperature in southwest Asia projected to exceed a threshold for human adaptability Nat. Clim. Change 18203 1–4
[26] Im E S, Pal J S and Eltahir E A B 2017 Deadly heat waves projected in the densely populated agricultural regions of South Asia Sci. Adv. 3 1–8
[27] Kang S and Eltahir E A B 2018 North China plain threatened by deadly heatwaves due to climate change and irrigation Nat. Commun. 9 2894
[28] Willett K M and Sherwood S 2012 Exceedance of heat index thresholds for 15 regions under a warming climate using the wet-bulb globe temperature Int. J. Climatol. 32 161–77
[29] Sherwood S C and Huber M 2010 An adaptability limit to climate change due to heat stress Proc. Natl. Acad. Sci. 107 9552–5
[30] Raymond C, Singh D and Horton R M 2017 Spatiotemporal patterns and synoptics of extreme wet-bulb temperature in the contiguous United States J. Geophys. Res. Atmos. 122 13108–24
[31] Seneviratne S I, Lüthi D, Litschi M and Schär C 2006 Land–atmosphere coupling and climate change in Europe Nature 443 205–9
[32] Ukkola A M, Pitman A J, Donat M G, De Kauwe M G and Angélou O 2018 Evaluating the contribution of land–atmosphere coupling to heat extremes in CMIP5 models Geophys. Res. Lett. 45 9003–12
[33] Taylor K E, Stouffer R J and Meehl G A 2012 An overview of CMIP and the experiment design Bull. Am. Meteorol. Soc. 93 485–98
[34] Moss R H et al 2010 The next generation of scenarios for climate change research and assessment Nature 463 747–56
[35] Davies-Jones R 2008 An efficient and accurate method for computing the wet-bulb temperature along pseudoadiabats Mon. Weather Rev. 136 2764–85
[36] Buzan J R, Oleson K and Huber M 2015 Implementation and comparison of a suite of heat stress metrics within the community land model version 4.5 Geosci. Model Dev. 8 151–70
[37] Kopp R E Wet bulb calculation (http://www.bobkopp.net/software/)
[38] O’Neill B C et al 2014 A new scenario framework for climate change research: the concept of shared socioeconomic pathways Clim. Change 122 387–400
[39] Jones B et al 2016 Spatially explicit global population scenarios consistent with the Shared Socioeconomic Pathways Environ. Res. Lett. 11 084003
[40] Donat M G, Pitman A J and Angélou O 2018 Understanding and reducing future uncertainty in mid-latitude daily heat extremes via land surface feedback constraints Geophys. Res. Lett. (https://doi.org/10.1029/2018GL079128)
[41] Byrne M P and O’Gorman P A 2018 Trends in continental temperature and humidity directly linked to ocean warming Proc. Natl. Acad. Sci. 115 4863–8
[42] Horton D E et al 2015 Contribution of changes in atmospheric circulation patterns to extreme temperature trends Nature 522 465–9
[43] Fischer E M and Knutti R 2012 Robust projections of combined humidity and temperature extremes Nat. Clim. Change 3 126–30
[44] Kunreuther H et al 2013 Risk management and climate change Nat. Clim. Change 3 447–50