Earth's Future

RESEARCH ARTICLE
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Key Points:
- Hazard from temporally compound heat waves will disproportionately increase with global warming
- Increase is controlled by mean shift in temperature and average local weather, not change in weather
- Vulnerability from prior heat waves should be considered in assessing heat wave risk

Supporting Information:
- Supporting Information S1

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Temporally Compound Heat Wave Events and Global Warming: An Emerging Hazard

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Abstract The temporal structure of heat waves having substantial human impact varies widely, with many featuring a compound structure of hot days interspersed with cooler breaks. In contrast, many heat wave definitions employed by meteorologists include a continuous threshold-exceedance duration criterion. This study examines the hazard of these diverse sequences of extreme heat in the present, and their change with global warming. We define compound heat waves to include those periods with additional hot days following short breaks in heat wave duration. We apply these definitions to analyze daily temperature data from observations, NOAA Geophysical Fluid Dynamics Laboratory global climate model simulations of the past and projected climate, and synthetically generated time series. We demonstrate that compound heat waves will constitute a greater proportion of heat wave hazard as the climate warms and suggest an explanation for this phenomenon. This result implies that in order to limit heat-related mortality and morbidity with global warming, there is a need to consider added vulnerability caused by the compounding of heat waves.

Plain Language Summary Heat waves are multiday periods of extremely hot temperatures and among the most deadly natural disasters. Studies show that heat waves will become longer, more numerous, and more intense with global warming. However, these studies do not consider the implications of multiple heat waves occurring in sequence, or "compounding." In this study, we analyze physics-based simulations of Earth's climate and temperature observations to provide the first quantifications of hazard from compound heat waves. We demonstrate that compound events will constitute a greater proportion of heat wave risk with global warming. This has important policy implications, suggesting that vulnerability from prior heat waves will be increasingly important to consider in assessing heat wave risk and that heat wave warning systems that currently primarily consider future-predicted weather should also account for the recent history of weather.

1. Introduction

1.1. Background

Heat waves—multiple, consecutive, hot days—present a significant threat to human health. Both multi-country and smaller-scale regional studies demonstrate that heat waves result in elevated mortality and morbidity (e.g., Anderson & Bell, 2009; Burgess et al., 2011; Deschenes & Greenstone, 2011; Fuhrmann et al., 2016; Gasparrini et al., 2015; Lippmann et al., 2013; Merte, 2017; Son et al., 2012). Of the 11 most deadly natural hazards in the continental United States, heat waves (here including those coupled with drought) constitute a plurality (~20%) of the mortality (Borden & Cutter, 2008). Heat stress is often exacerbated by electric power disruptions, which interrupt air conditioning (A/C; Aivalioti, 2015; van Vliet et al., 2012). Extremely high temperatures decrease yields of major crops such as corn, soybean, and cotton and reduce productive and reproductive efficiency of livestock (Battisti & Naylor, 2009; Fuquay, 1981; Kadzere et al., 2002; Lobell et al., 2011; Schlenker & Roberts, 2009). Despite these impacts, heat waves often do not receive significant media attention, possibly because they are not visually spectacular and also because they tend to affect underserved members of the population such as elderly, racially marginalized, sick, and/or socially isolated individuals (Fouillet et al., 2006; Semenza et al., 1996). Ongoing sociological trends are expected to increase populations vulnerable to heatwaves (we use the terms hazard, vulnerability, exposure, and risk in this paper consistent with the way those terms are defined in Oppenheimer et al., 2014). For example,

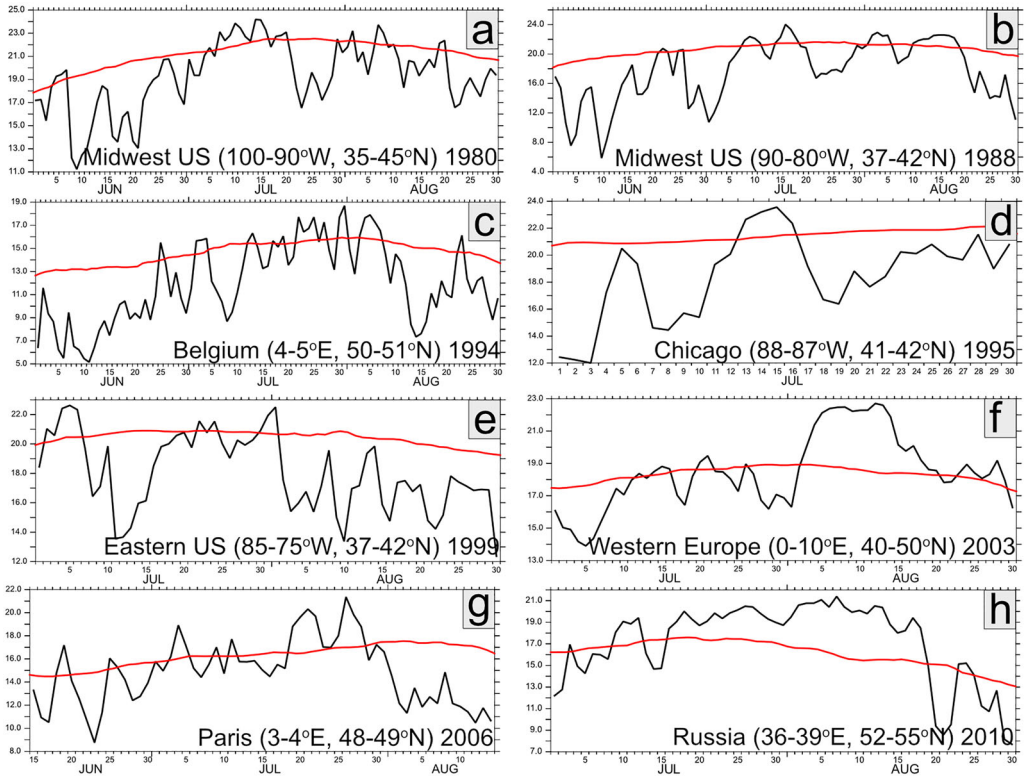

Figure 1. Past heat waves that resulted in high mortality. MERRA2 daily minimum temperature (black) and the corresponding seasonally varying thresholds (red) are averaged over regions and plotted against summer days. The location name, latitude-longitude range, and year of each heat wave are listed at the bottom of each panel. These heat waves were chosen to illustrate temperature time series for the four most deadly heat waves in Europe and the United States since 1980 (see Table S1 for mortality estimates). These events were initially selected by aggregating information from NCEI, Masters (2015), Sartor et al. (1995), and Klinenberg (2015).

especially in developed countries, populations are aging (Anderson & Hussey, 2000), and individuals are increasingly isolated from close family or friends (McPherson et al., 2006).

The severe impacts of heat waves have motivated research to characterize, understand, and predict them. Major heat waves in the midlatitudes typically result from blocking highs (quasi-stationary anticyclones) further amplified via moisture deficit (Black et al., 2004; Fink et al., 2004; Hirschi et al., 2011; Quesada et al., 2012; Schar et al., 2004). Over continental regions in the Northern Hemisphere, 80% of warm temperature extremes are associated with these atmospheric blocking patterns (Pfahl & Wernli, 2012). Diverse modes of variability of the climate system, such as the El Niño-Southern Oscillation and the North Atlantic Oscillation, modulate these synoptic patterns and in turn influence heat waves (Grotjahn et al., 2015; Hsu et al., 2017; Kenyon & Hegerl, 2008; Loughran et al., 2017). Additionally, heat waves are often exacerbated over populous regions due to urban heat island effects (Ramamurthy et al., 2017; Zhao et al., 2017).

Global warming from increasing greenhouse gasses has and will continue to increase heat wave hazards. Increases in heat wave frequency, duration, and intensity have already been observed (Perkins et al., 2012), and numerous attribution studies demonstrate that global warming has increased the probability of recent major heat waves (e.g., Jaeger et al., 2008; Meehl & Tebaldi, 2004; Stott et al., 2004). As an example, the summer 2010 Russian heat wave was reportedly responsible for ~56,000 deaths (Gutterman, 2010; Rahmstorf & Coumou, 2011); the July monthly temperature record associated with this event is estimated to have been five times more likely due to the warming that has occurred since preindustrial times (Otto et al., 2012; Rahmstorf & Coumou, 2011). By the end of this century, following the Representative Concentration Pathway 8.5 emissions scenario ("business-as-usual"), heat waves with duration and temperature anomaly magnitude comparable to this event are expected to occur every few years in many regions across the globe (Russo et al., 2014). With global mean warming of 2 °C, the upper bound recommended by the Paris Agreement of the United Nations Framework Convention on Climate Change, many tropical locations

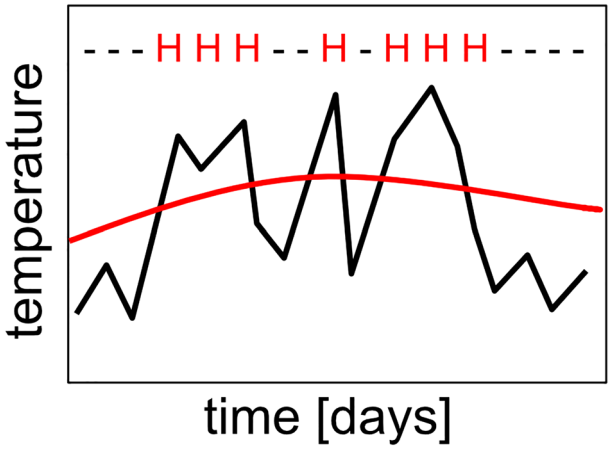

Figure 2. Schematic temperature time series to build intuition regarding the heat wave definitions. Cartoon temperature (black) and a seasonally varying threshold (red) are plotted against time. At the top of the figure, threshold-exceeding hot days are marked with red Hs while below threshold cooler days are marked with black minus signs. According to the Warm Spell Duration Index no heat wave occurs, as the events are too short. According to another prior heat wave definition (i.e., Perkins & Alexander, 2012) this would constitute two 3-day-long heat waves. In this paper we count this event as having a total duration of 7 days, composed of an initial 3-day-long heat wave with four additional hot days compounded onto it.

will already be enduring a constant heat wave state, with no or very few days a year below extreme hot day thresholds (Perkins-Kirkpatrick & Gibson, 2017).

Both changes to the mean and higher-order moments of temperature distributions can influence heat wave hazards. Trends in higher-order moments (such as variance) might result from interplay between the radiative effects of increased CO_2, circulation changes, and land-atmosphere interactions. In places with moderate levels of soil moisture, projected summertime drying is expected to increase surface temperature response to circulation anomalies, and in turn likelihood of heat events (e.g., Dirmeyer et al., 2012; Quesada et al., 2012; Seneviratne et al., 2010). Trends also may exist in the blocking events and other circulation anomalies associated with heat waves (Coumou et al., 2014, 2015; Hoskins & Woollings, 2015; Petoukhov et al., 2013; Pfahl et al., 2015). However, these trends remain speculative, as the observed period is short and climate model results are inconsistent (Horton et al., 2016). Overall, diverse phenomena might make temperature variability change alongside mean warming, but how and why is still highly uncertain.

1.2. Motivation and Goals of This Study

A necessary first step and complication in studying heat waves are defining them. Common to most definitions is the choice of a threshold above which a day's temperature, or a thermal stress metric, is considered hot. If a minimum number of hot days occur in a row, then a heat wave is said to have occurred. Heat wave hazard then is the count of days meeting these requirements that occur over a period of time. As a specific example, one definition measuring heat wave duration is the Warm Spell Duration Index (WSDI), which uses a seasonally varying 90th percentile temperature threshold and requires at least six threshold-exceeding days in a row (see the supporting information for further definition details and alternatives; Sillmann et al., 2013b). For the rest of this paper we refer to days that exceed an assigned temperature threshold as "hot days," and a set of hot days occurring close in time meeting certain duration requirements as a "heat wave."

Temperature time series for major historical heat waves are compared to a corresponding local temperature threshold in Figure 1. We use the WSDI threshold as an instructive example, but other common hot day thresholds would produce similar results. According to our review of the existing literature, the heat waves depicted in Figure 1 are the four deadliest heat waves in Europe and the United States since 1980 (see the supporting information for mortality estimates). Of the events, only Western Europe in 2003 and Russia in 2010 clearly meet the six continuous hot days requirement of WSDI, and these were indeed associated with the first and second highest mortality among the eight. Chicago in 1995 just misses the duration requirement, with five threshold-exceeding hot days. The other deadly heat waves included in Figure 1 exhibit more exotic temporal structures that do not appear to be well described by the continuous hot days requirement of WSDI and other heat wave definitions, with temperature dipping below the threshold multiple times (Belgium in 1994 is a particularly striking example). This suggests that temperature extremes that occur close in time with short break periods of cooler days in between might compound together to create impacts similar to more consistent hot periods recognized by standard heat wave duration definitions. This variable temporal structure resulting in high mortality also may point to heightened vulnerability to subsequent temperature extremes after an initial heat wave.

Here we characterize heat waves with intermittent temporal structures as a type of compound extreme event (Figure 2 gives a cartoon example of this type of event to build intuition). Broadly, a compound extreme event is a combination of climatic events that together constitute an extreme event in terms of the associated climatic anomaly or impacts. Even though many past climate-related natural disasters are best characterized as compound extreme events (Leonard et al., 2014), such events and their future change are relatively understudied (Field, 2012; Zscheischler et al., 2018). Recent work has made some advances in this area, including joint projections of temperature and humidity (Fischer & Knutti, 2013), storm surge associated with tropical cyclones combined with sea level rise to predict extremes of high water (Little et al., 2015),

extreme storm surge and precipitation events (Wahl et al., 2015), the possibility of disasters occurring in multiple bread baskets at once and affecting world food supply (Lunt et al., 2016), and clustered outbreaks of tornadoes (Tippett et al., 2016). In this paper we focus on temporally compound heat wave events, that is, multiple heat extremes occurring in sequence in a particular location with intermittent short breaks.

To understand risk from temporally compound heat waves, a few different key questions remain to be answered, including (1) what is the physical hazard from compound heat waves in the present, (2) how will this hazard change with global warming, (3) what is the relationship in the present between compound heat waves and various impacts (e.g., mortality and agricultural yields), and (4) how will the impacts of compound heat waves change with global warming. Our aim in this work is to answer the first two questions regarding the physical hazard of compound heat waves. In other words, we study one component of compound heat wave risk, the hazard, but leave close examinations of the vulnerability and exposure associated with these events to future work. We generally characterize this hazard as the number of hot days that are part of compound heat waves. While some studies use more flexible heat wave definitions that can allow for short breaks of cooler days within the event (Lau & Nath, 2012, 2014; McKinnon et al., 2016a; Meehl & Tebaldi, 2004), these have not focused on the diverse temporal structures and compounding of extreme heat events, hence the new contribution of this work. Additionally, we perform further analysis to understand whether changes in mean or higher-order moments of temperature underpin projected trends in compound heat waves. This additional examination helps evaluate the robustness of our results and elucidate what physical mechanisms are relevant to the trends in these events.

While we do not quantify compound heat wave impacts in this study, our results strongly motivate their examination in future work. We demonstrate that with global warming there will be a robust increasing trend of both the absolute compound heat wave hazard, and proportion of compound hazard relative to total heat wave hazard. It is as yet unclear if all else being equal (i.e., for the same number of extremely hot days) more compound events imply higher risk. This would be the case if risks from heat waves occurring closer in time add nonlinearly. In the existing literature there are hints of heightened vulnerability from prior heat waves, which could plausibly create nonlinear addition of the impacts of these individual heat waves. For example, Ramamurthy et al. (2017) shows that temperature within apartments in New York City remains elevated even a few days after a period of extreme heat has passed, heightening risk for those individuals staying indoors to a latter heat wave. We hypothesize that following an initial heat wave aspects of the built environment, human body, and social systems might all heighten vulnerability to later heat waves. The discussion of this paper more systematically outlines possible sources of this vulnerability, providing a number of directions for future work investigating impacts of these events.

The rest of this paper is structured as follows: Section 2 presents our methods, including our compound heat wave definitions and the temperature data utilized; section 3 presents our results, exploring compound heat wave events in the present and their projected change with global warming, and mechanisms behind their change; and finally, section 4 discusses the results in the context of prior analysis of temperature extremes, examines relevance for heat wave impacts and policy, and suggests directions for future work.

2. Methods

2.1. Compound Heat Wave Definitions

Our definition uses the same seasonally varying threshold structure as WSDI but modifies the requirement of consecutive days via additional parameters. The condition of a minimum number of hot days occurring in a row to constitute a heat wave is instead replaced with (1) a minimum number of hot days occurring consecutively to start a heat wave, (2) a maximum number of cooler (below threshold) days that can occur consecutively for the heat wave to continue, and (3) a minimum number of hot days occurring consecutively that can add onto a heat wave after a break. Multiple breaks are allowed in a single heat wave provided the additional days follow conditions 2 and 3 above. For quick reference, we denote a temporal structure definition with three numbers, for example, 321, where 3 indicates a minimum initial event length of three hot days, 2 indicates a maximum break length of two cooler days, and 1 indicates a minimum length of a set of consecutive hot days that can compound on after a break.

This new definition includes parameters unconstrained by prior work. These could be constrained by drawing correlations with an impact of interest, such as morbidity or seeking to generate meteorological events of a certain rarity. Given the dearth of work on temporal structure of heat waves and their compounding,

Table 1
Options for the Temporally Flexible Heat Wave Definition

Definition parameter	Options
Temperature data	Daily minimum, daily maximum
Threshold percentile	90th, 95th
Minimum initial heat event duration	1, 3, or 6 days
Maximum break duration	1, 2, or 3 days
Minimum subsequent heat event duration	1, 3, or 6 days

Note. We test definitions using all combinations of the parameter options shown here. Note that we refer to days that exceed the threshold as hot days, and a set of consecutive hot days plus hot days separated by short breaks as a heat wave.

we instead vary the parameters and report conclusions that are robust across that parameter range. All the definition parameters that we vary are summarized in Table 1. In addition to the temporal structure parameters described in the prior paragraph, we also test using daily minimum versus daily maximum temperature data, and different percentile threshold levels. Further justification for the choice of threshold, definition temporal structure parameters, and range of parameter values is given in the supporting information.

Once we find hot days in events meeting our definition, we calculate two quantities: the cumulative total number of hot days occurring in heat waves each year (hereafter "heat wave days") and the number of these hot days that occur in subsequent events that add onto prior heat waves after short breaks, which we will refer to as "compound days" (Figure 2). The quantity of interest here is the cumulative annual compound days as a proportion of total heat wave days (hereafter "compound proportion"). This compound proportion represents the proportion of heat wave risk subject to vulnerability from prior hot days separated by cooler breaks.

We only calculate these quantities from the summer months (May–September in the Northern Hemisphere and November–March in the Southern Hemisphere) to simplify the meteorological interpretation and because heat-related morbidity and mortality are the primary impacts of interest. As a result, the maximum length of a heat wave in our study is the entire summer (153 days). We use different months for our calculations in the Northern versus Southern Hemispheres primarily because it is the simplest way to account for the strong seasonality of the extratropics. In reality the whole year contributes to heat wave risk in the tropics where the amplitude of the seasonal cycle is very low, and so our set up might be improved by calculating tropical heat waves from the whole year. However, we do not think this assumption alters the key results described in this study. We also only calculate these metrics over land points, excluding ocean points in regional averaging.

2.2. Temperature Data

In this study we apply our heat wave definitions to three types of data: global climate model (GCM) output, observationally derived reanalysis to validate the GCM's simulation of heat wave statistics, and synthetic time series generated from statistical models to help interpret results from the GCM data. These are described below.

2.2.1. Climate Model Simulations

The GCM used for this study is CM2.5-FLOR (hereafter FLOR), which is the Forecast-oriented Low Ocean Resolution derivative of CM2.5 (Delworth et al., 2012). It has a relatively high resolution ~50-km atmosphere and land and a relatively low resolution ~1° ocean (Jia et al., 2015; Vecchi et al., 2014). The relatively high land/atmosphere resolution of FLOR allows it to simulate finer spatial and temporal scales of temperature variability (Jia et al., 2015). However, urban heat island effects are not captured. This family of models' simulation of a variety of climatic phenomena has been examined and validated. Most relevant are prior studies using these models to examine the heat waves in 2006 and 2012 over the contiguous United States and their climatic drivers (Jia et al., 2016), the predictability of temperature and precipitation over land (Jia et al., 2015), and precipitation extremes over land (van der Wiel et al., 2016).

Two sets of experiments are used in this study. The first is a five-member ensemble initialized in year 1861 and simulating through 2100 following the Representative Concentration Pathway 4.5 scenario from year 2006 onward (Jia et al., 2016). This ensemble is employed to validate FLOR's simulation of heat wave events. The second are two idealized radiative forcing simulations (He et al., 2017): "control," in which atmospheric

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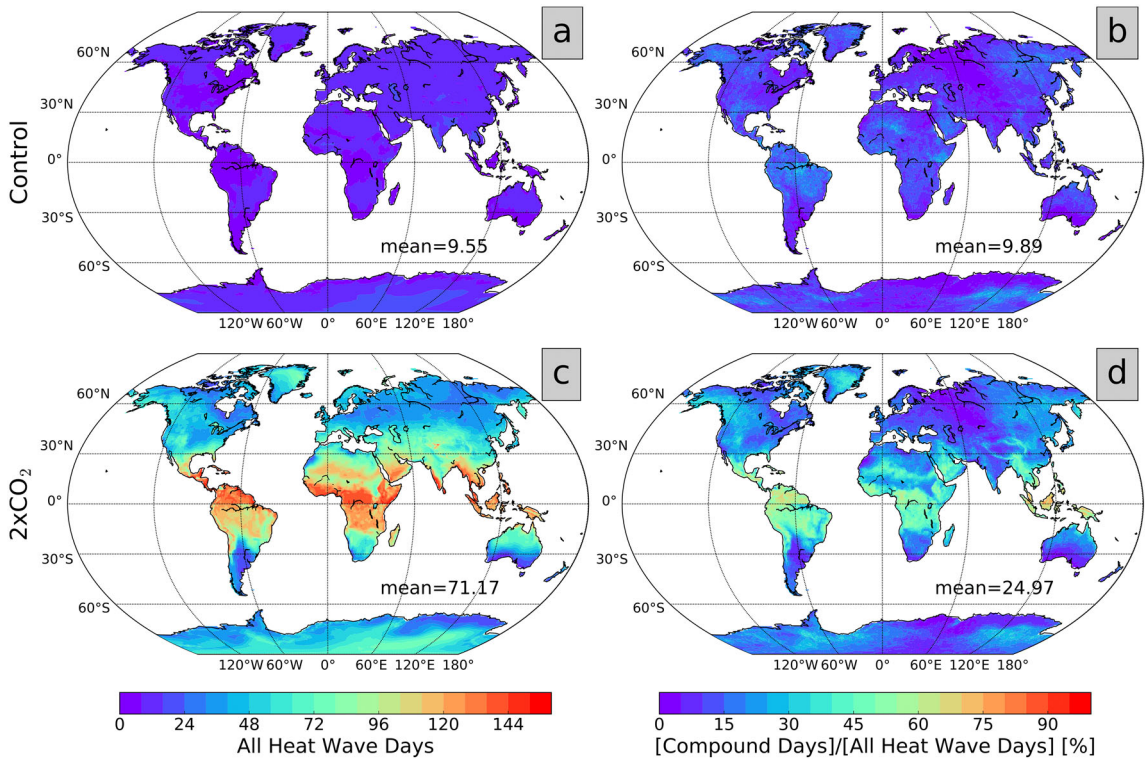

Figure 3. FLOR output heat wave hazard and compound proportion. Control (a and b) and 2xCO_2 (c and d) total summer heat wave days (a and c) and proportion of those heat wave days that are compounded in percent terms (b and d), calculated from all 100 years of the model daily minimum temperature data. Daily minimum temperature data are used, the temporal structure definition is 311, and the threshold is the seasonally varying 90th percentile calculated from years 1981–2010, but qualitative results are robust across the range of definitions tested. Global means are noted on each panel.

levels of CO_2 are kept constant at year 1990 levels, and "2xCO_2," in which CO_2 is increased to twice 1990 levels and then held constant. For the ensemble, the threshold is calculated from each individual ensemble member, and for the idealized simulations the threshold is calculated from control and applied to both control and 2xCO_2. See the supporting information for further details.

2.2.2. Observationally Derived Data Sets

To validate FLOR's simulation of temperature extremes, we use NASA's Modern-Era Retrospective analysis for Research and Applications, version 2 (MERRA2) reanalysis, which provides daily maximum and minimum temperature computed on the model time step at a 0.625° by 0.5° resolution from 1980 to the present (Global Modeling and Assimilation Office, 2015). Data from years 1981–2010 (same years as the FLOR ensemble) are used to calculate the MERRA2 hot day threshold.

2.2.3. Synthetic Time Series

To generate synthetic temperature data, we use the autoregressive lag 1 model (AR1; see the supporting information). Analogous time series to the control and 2xCO_2 simulations are created by shifting the mean of the AR1 synthetic time series. The AR1 time series are generated for the same temporal length, range of autocorrelation, and range of variance normalized by mean shift as the FLOR data then analyzed using our heat wave definitions.

3. Results

We present the following analyses of compound heat waves: (a) validation of GCM simulation, (b) projections from GCM data, (c) synthetic data analysis to aid understanding, and (d) projections from observed data. When only results from one compound heat wave definition are shown, that definition is 311 temporal structure derived from daily minimum temperature data with a 90th percentile threshold. However, the qualitative conclusions discussed are robust across the range of definition parameter settings shown in Table 1.

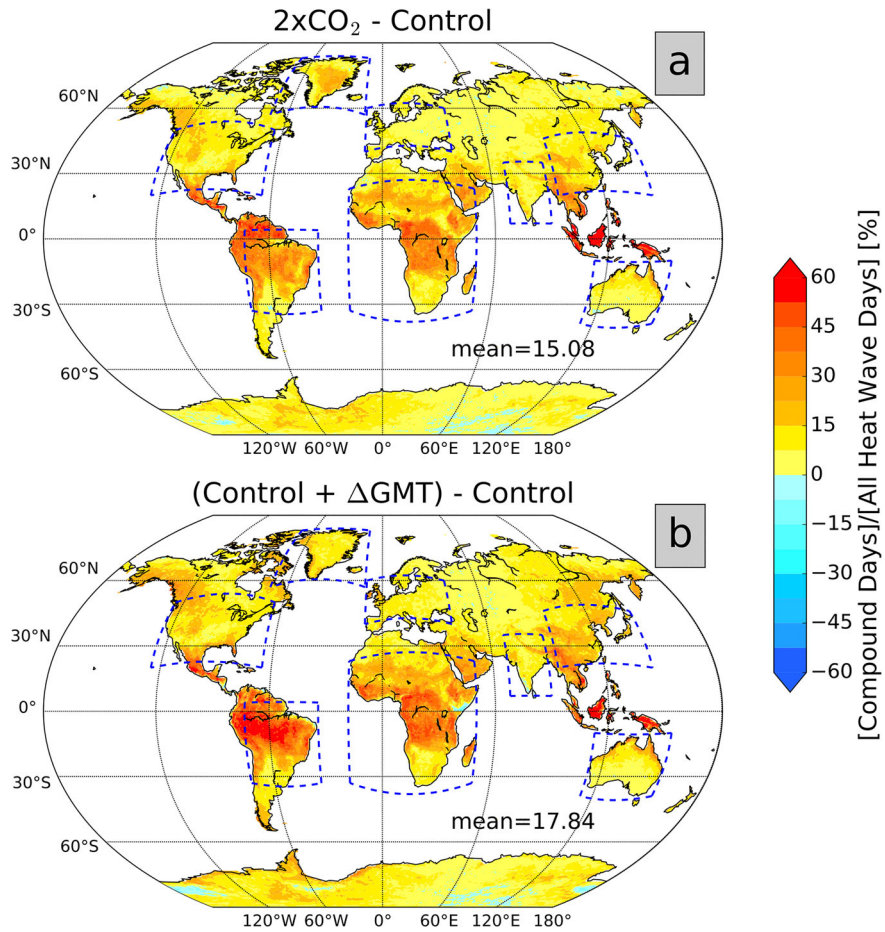

Figure 4. Change in compound proportion and bias from synthetically shifting the mean. Differences are shown in compound proportion (%) between the $2xCO_2$ and control simulations (a; difference between Figures 3b and 3d) and the control simulation and control + ΔGMT (b). Daily minimum temperature data are used, the temporal structure definition is 311, and the threshold is the seasonally varying 90th percentile calculated from years 401–430 of control, but qualitative results are robust across the range of definitions. The blue dashed rectangles designate regions over which spatial correlations are calculated in Figure 5. GMT = global mean temperature.

3.1. GCM Validation

Overall, FLOR simulates mean heat wave days and trends in the United States and Western Europe quite well but has high biases outside of these regions (see the supporting information). It is difficult to disentangle whether the differences between the reanalysis and model data result from model biases, reanalysis biases, or MERRA2 representing only one realization of internal variability compared to the average of many realizations in the model ensemble. Fortunately, the bias in the metric of most interest, compound proportion, is generally small. We move forward using FLOR as an initial examination of compound heat wave events, but given these biases acknowledge the need for further verification of our results with other models and observations.

3.2. GCM Sensitivity

In control, the heat wave days are relatively few (only about 10 days per summer; Figure 3a), and only about one of these days (10%) is compounded onto prior hot days (Figure 3b). This is similar to the compound days and proportion found over the observed period using MERRA2 (Figure S1). In contrast, in $2xCO_2$, there are on average about seven times as many heat wave days each summer as in control. This increase in heat wave days is expected, given that the hot day threshold computed from control is applied to both control and the much warmer $2xCO_2$ simulation. The greatest increase in heat wave days occurs in the tropics, consistent with prior studies (Sillmann et al., 2013a). The tropics have low variance in temperature relative to the extratropics; thus, an increase in mean temperature approaches the limit of moving the entire tempera-

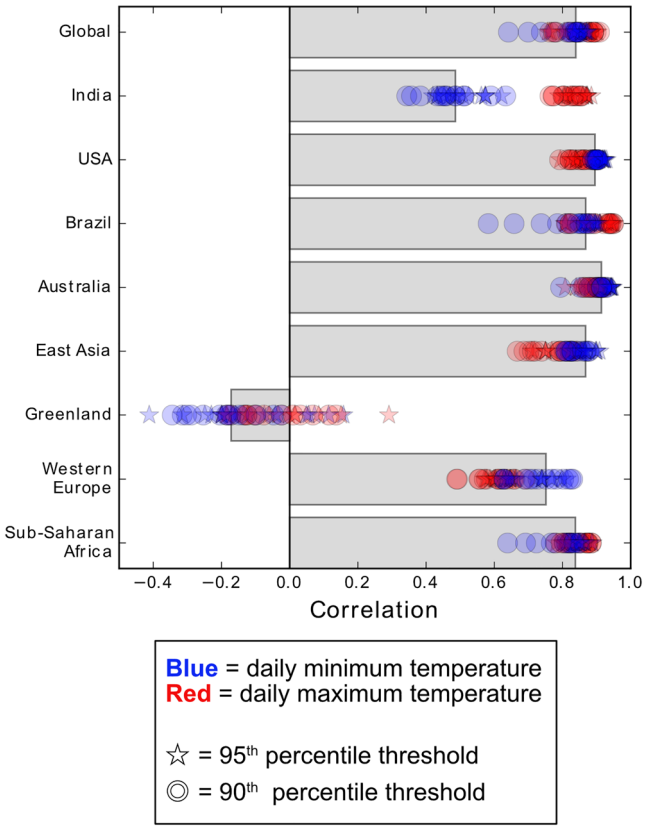

Figure 5. Spatial correlation of 2xCO_2-control and (control + ΔGMT)-control compound proportion over the globe and various smaller regions. The regions over which the spatial correlations are calculated are shown in Figure 4. The gray bars designate the spatial correlation calculated for the definition used in Figure 4 (daily minimum temperature, 90th percentile threshold, 311), and the markers represent spatial correlations calculated for the full range of definition variants. Blue and red designate daily minimum and maximum temperature, and stars and circles designate 90th and 95th percentile thresholds, respectively; temporal structures are not noted but include the full parameter space of Table 1. GMT = global mean temperature.

ture time series above the hot day threshold. To help demonstrate this, examples from specific tropical and extratropical locations are shown in Figure S7.

In addition to the higher total number of heat wave days in 2xCO_2, the proportion of hot days compounded onto prior heat waves is also higher—global-time mean of 25% in 2xCO_2 versus 10% in control (Figure 3d). As with the total number of heat wave days, the greatest increases in compound proportion tend to occur in the tropics (Figure 4a). The increase in compound proportion is also robust across all tested definition parameter values (Figure S5).

3.3. Understanding the Increase in Compound Proportion

In seeking to explain these behaviors we consider both the physical characteristics of the system and the statistical properties of temperature time series. Observed temperature trends over the past few decades are primarily explained by a shift in the mean, though limited change in higher-order moments of temperature has occurred as well (McKinnon et al., 2016b). Simply increasing the mean of a temperature time series, such as those in Figure 1, would result in more exceedances above the threshold (hot days) with those hot days occurring closer together, increasing the proportion of compound days. Such a mean shift could result just from the radiative changes associated with increasing carbon dioxide, without any complicated local feedbacks. Another possible explanation we need to consider is that the changes in higher-order moments of the temperature time series (i.e., weather) lead the hot days to be clustered closer together, increasing the proportion of compound days. Changes in higher-order moments would likely reflect more complex and local mechanisms, such as land-atmosphere interactions or circulation changes (see section 1 for background). In particular, we hypothesized that with warming a heat wave might dry out the land surface more than in

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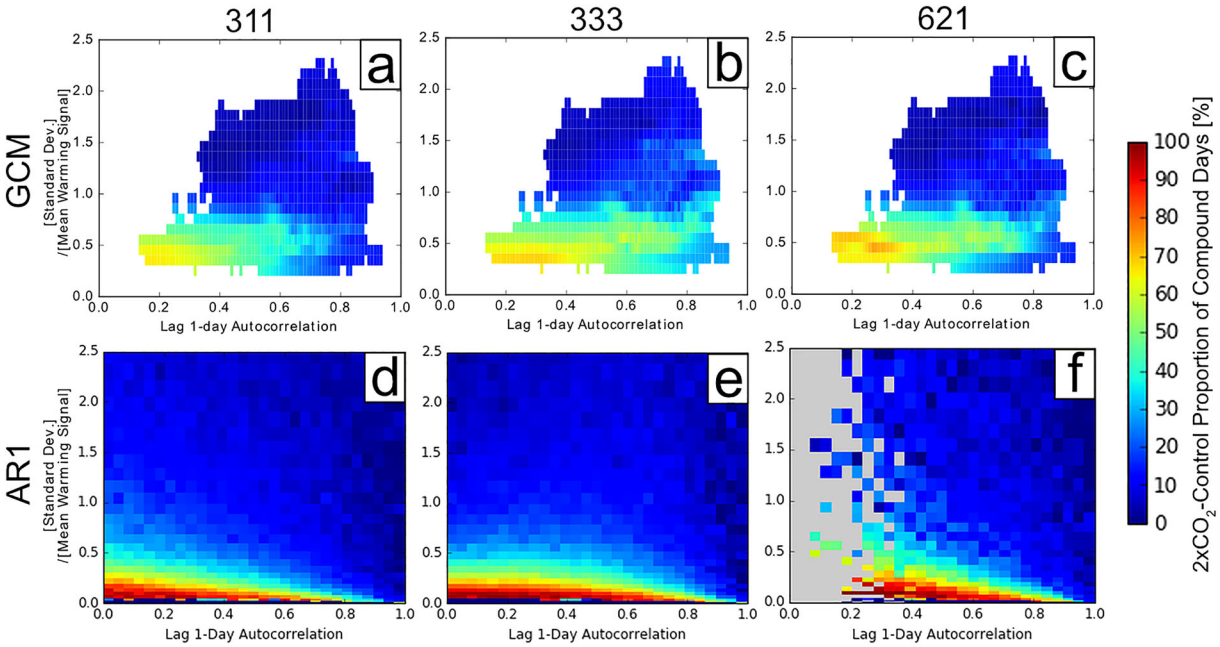

Figure 6. Influence of autocorrelation and variance on change in compound proportion. Change in compound proportion with warming is shaded and plotted against lag 1-day autocorrelation and standard deviation normalized by mean warming. For the GCM, FLOR, data (a–c), lag 1-day autocorrelation, and standard deviation are calculated from the control simulation at each location. For the AR1 synthetic data, standard deviation and mean warming are assigned to be consistent with the GCM data, while autocorrelation is varied across the full possible range (0–1). Three temporal definitions are used: 311 (a and d), 333 (b and e), and 621 (c and f). For the 621 definition, some of the AR1 synthetic time series at lower autocorrelations are not able to generate long enough periods of hot days to meet the definition event duration requirements particularly for the "control" climate; where this occurs, the shaded compound proportion is colored gray. GCM = global climate model.

the past, exacerbating temperature extremes of a subsequent heat event through latent-sensible heat flux partitioning and making heat waves more likely to cluster together and compound.

To test these potential explanations, we shift the mean of control temperature to equal the mean of $2xCO_2$ temperature and compare the mean shifted control to $2xCO_2$ heat wave results. We calculated the mean shift (i.e., $2xCO_2$-control for daily minimum or maximum temperature) in a few different ways: (1) global-time mean, (2) time mean spatially varying, and (3) daily climatology spatially varying. In all cases we calculate the mean shift over land locations excluding the ocean. We only found minor improvements with the more complex methods of calculating the mean shift (Figure S6), so we will focus on results from adding the global-time mean difference between $2xCO_2$ and control to control (hereafter control + ΔGMT where GMT = global mean temperature).

We find that spatial variations of the change in compound proportion for $2xCO_2$-control are well approximated by (control + ΔGMT)-control (Figures 4 and 5). Across the globe and various versions of the heat wave definition, the pattern correlation is quite high—close to 0.8. For particular regions, the pattern correlation and thus success of the mean shifting approximation vary. The approximation is quite accurate over most highly populated regions and especially over the United States and Australia (correlation ~0.9). In contrast, Greenland has a negative pattern correlation for many definitions. We hypothesize this arises from Greenland's ice melting with warming, an effect not captured with our simple approximation. India presents a particularly interesting response, with a high correlation for daily maximum temperature (~0.8), but a low correlation for daily minimum temperature (~0.4). We suggest that the strong seasonality of cloudiness and rainfall due to the South Asian Monsoon could be responsible for this effect. Acknowledging these biases, shifting the mean of the temperature data reasonably captures the sign, magnitude, and pattern of change in compound proportion with increasing atmospheric CO_2.

This suggests that spatial variations in daily temperature variability (i.e., weather) drive the spatial variation in compound proportion change with warming, while weather changes and the pattern of mean warming are of secondary importance. We hypothesized that the spatial structure of the temperature time series memory and variance might essentially describe the relevant local weather. To test this hypothesis, we use

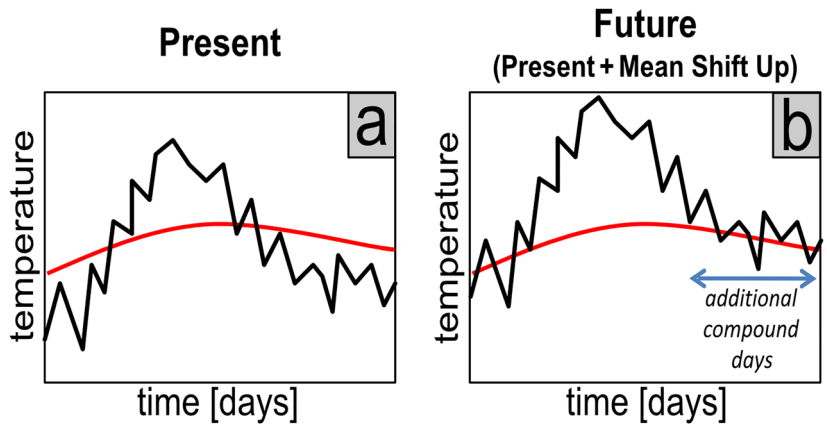

Figure 7. Mechanism for change in proportion of compound days. Cartoon temperature time series and threshold in original (e.g., preindustrial) climate (a), and after increase in CO_2 (b). To a reasonable approximation, the change in the proportion of compound days can be understood as the result of the mean shift of a time series resulting in more threshold exceedances, and hence those threshold exceedances occurring closer together. Note that the type of changes shown in this schematic is also demonstrated with global climate model output in Figure S7.

the synthetic AR1 time series. We find there are some key similarities in the relationship between variance, autocorrelation, and change in compound proportion for the AR1 and FLOR data. Change in compound proportion is generally greatest at the low-autocorrelation, low-variance limit, decreasing as variance and autocorrelation increase (Figure 6). With low variance, excursions of the time series over any individual day are small; with low autocorrelation, the same is true for series of days. Mean shifts then easily approach the limit of moving the whole temperature time series above the threshold with warming, generating large changes in heat wave days and compound proportion. This is consistent with the highest changes in compound proportion occurring in the tropics (Figure 4), where the synoptic variability of the atmosphere is low.

Altogether, in the present climate when a heat wave occurs, it likely requires a system with some memory (i.e., blocking high) to create an increase in temperature sufficiently large and long lasting (Figure 7a). In contrast, in the future warmed climate, the mean is sufficiently close to the threshold that typical weather variations can result in threshold exceedances, and in turn a greater proportion of compound days (Figure 7b). In other words, given there are more hot days, those hot days occur closer together in time and are more likely to compound. Notably, this explanation relies on a quite simple physical mechanism, namely, increase of mean temperature with higher levels of carbon dioxide, without relying on more complex changes in temperature time series associated with land-atmosphere interactions or circulation changes.

3.4. Projections from Observationally Derived Data

The main cause of spatial variation of the change in compound proportion is spatial structure of temperature time series variability. This suggests we may estimate future change in compound proportion simply by shifting the mean of observed temperature data, allowing us to explore particular policy-relevant levels of GMT increase. Projected changes in compound proportion applying a mean shift to the MERRA2 temperature data are shown in Figure 8. The mean temperature shifts examined include targets of the United Nations Framework Convention on Climate Change (1.5 and 2 °C; Hulme, 2016) and the ΔGMT found for CO_2 doubling in FLOR (2.7 °C; see the supporting information for details of how these shifts are applied). The FLOR control versus 2xCO_2 analysis of compound proportion change (Figure 4) and this analysis have complementary limitations. The FLOR analysis is biased in its underlying temperature time series (i.e., weather), while this MERRA2 analysis has a simplified warming. Thus, comparing Figures 4b and 8 provides a range of estimates applying different methodologies for compound proportion change.

CO_2 doubling in FLOR and 1.5 and 2 °C of GMT warming of MERRA2 exhibit large changes in compound proportion in the tropics, and smaller changes toward the poles. However, for the ΔGMT equivalent to a doubling of CO_2 in FLOR, MERRA2 counterintuitively exhibits a decrease in compound proportion in the tropics. This occurs when almost all summer days are extremely hot, so the number of heat waves saturates and starts to decrease to one summer-long long heat wave. This compound proportion decrease occurs first

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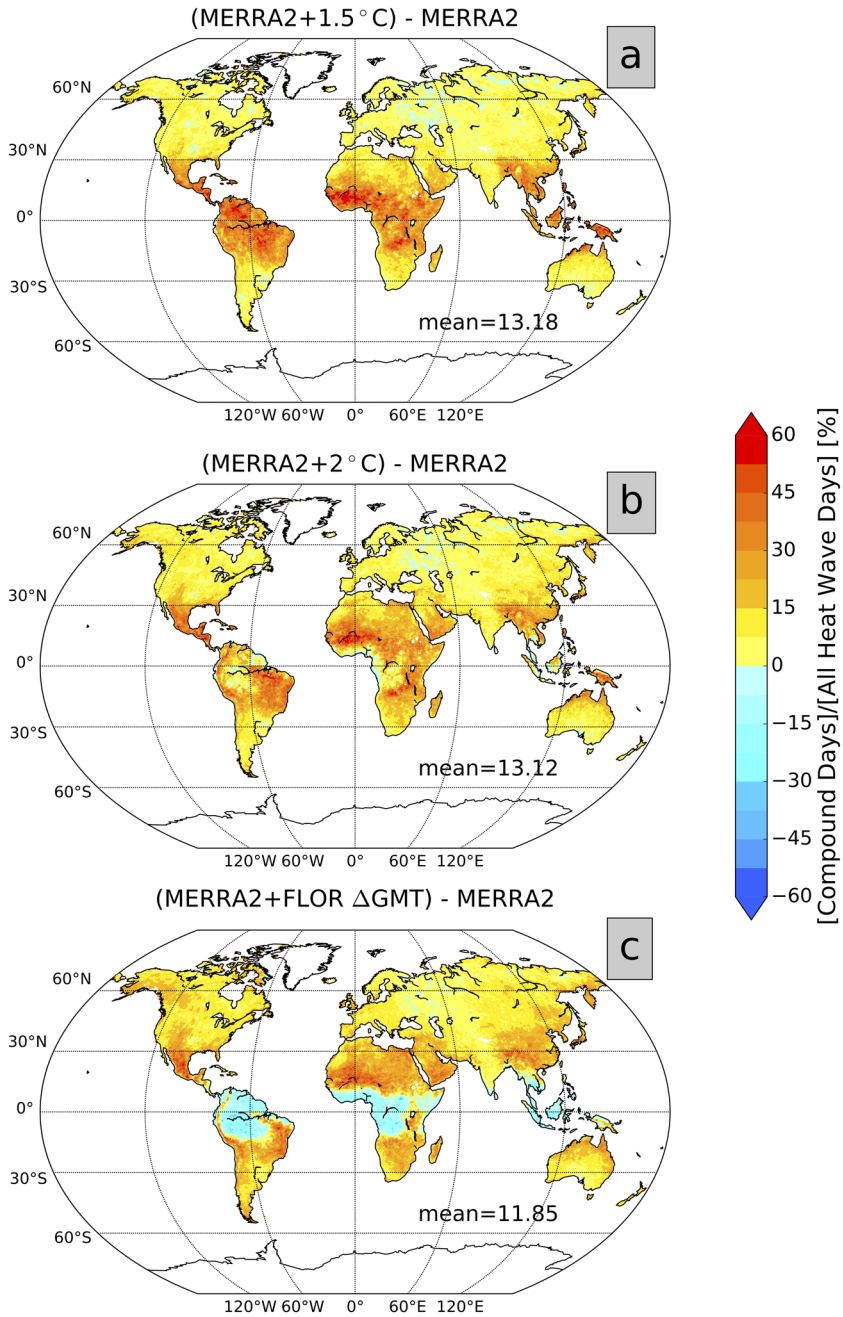

Figure 8. Change in compound proportion for MERRA2 with different amounts of warming. Temperature at all locations is increased by the estimated daily minimum temperature warming over land corresponding to global average near-surface warming of 1.5 °C (a), 2 °C (b), or that from the FLOR 2xCO_2 compared to its control (~ 2.7 °C; c), and then compared to the original MERRA2 data with no warming. Spatial means over locations with data are listed in each panel. Daily minimum temperature data is used, the temporal structure definition is 311, and the threshold is the seasonally varying 90th percentile calculated from years 401–430 of control, but qualitative results are robust across the range of definitions. GMT = global mean temperature; MERRA2 = Modern-Era Retrospective analysis for Research and Applications, Version 2.

in the tropics as temperature variance there is quite low. Relatedly, it is not found in FLOR until higher levels of warming (Figures 4, S8c, and S8d) because FLOR's tropical temperature variance is biased high compared to MERRA2 (Figure S3). For further intuition about these nonlinear changes in compound proportion with warming, please see the supporting information where we demonstrate these effects for specific tropical and extratropical locations. A similar saturation effect is described in Perkins-Kirkpatrick and Gibson (2017), which analyzes ensembles of GCM simulations reaching high levels of warming. These nonlinear changes with warming indicate a deficiency of certain threshold-based heat wave definitions in reflecting heat wave risk. If the hot day threshold is held constant (i.e., assuming no adaptation), the number of heat waves and compound proportion will start to decrease at high levels of warming, despite the fact that heat wave risk will presumably still be increasing.

4. Discussion

We demonstrate that the proportion of heat wave days that occur as hot days following short cooler breaks (i.e., compound proportion) will increase in a warming climate. This is a robust result that can be understood from a simple shift of the mean of a time series characterized by some memory and noise. Prior modeling (Lau & Nath, 2012, 2014) and observational studies (Huybers et al., 2014; McKinnon et al., 2016b; Rahmstorf & Coumou, 2011) have shown that changes in other characteristics of temperature extremes are largely explained by mean shifting without change in higher-order moments. This is true even though GCMs have significant biases in their simulation of meteorological events that influence temperature extremes (Chang et al., 2016; Grotjahn et al., 2015). Notably, mean shifting does not explain precipitation changes: in Europe, wet day clustering, not total number, drives recent wet/dry period changes (Zolina et al., 2012).

The uncertainty in future temperature extremes is typically quantified via a suite of different GCM projections, which capture relevant dynamic climate effects such as land-atmosphere interactions and changes in blocking (Flato & Marotzke, 2013). However, for the GCM used in this study these nonlinear changes in temperature with global warming are of secondary importance in setting the spatial pattern of changes in compound proportion. More important appears to be the structure of the local temperature time series in the present climate, which can be assumed to shift warmer with increased CO_2. An alternative method then of determining temperature extreme change uncertainty would be to take an observed or reanalysis temperature time series from the present, shift its mean across the distribution of GMT sensitivities to increasing CO_2, and then calculate the heat wave statistics. This is similar to the "Delta Method" of downscaling GCM data (Ramirez-Villegas & Jarvis, 2010) and is plausibly more accurate than, or at least complementary to, using the raw GCM projections, which have biases in their daily temperature time series structure.

We have provided this alternative projection of change in compound proportion by shifting the mean of the MERRA2 reanalysis data (Figure 8). For low levels of warming, the tropics exhibit greater increases in compound proportion than the extratropics, as was found for the GCM data. However, for higher levels of warming (between ~1.5 and 3.5 °C depending on location), this analysis suggests there will be a regime change in tropical locations, at which point every day in the summer will be hot and compound proportion will tend to zero due to the lack of breaks. In contrast, compound proportion continues to increase in the extratropics for the foreseeable future. This tropical-extratropical difference is rooted in the lower variance of temperature in the tropics, as was explored in the context of FLOR here and is consistent with prior studies (Lustenberger et al., 2014; Rahmstorf & Coumou, 2011; Wartenburger et al., 2017). The saturation of compound proportion with high levels of warming suggests that the usefulness of the metrics used in this analysis, along with other heat wave definitions, will need to be reevaluated as global warming progresses. It is possible that thresholds should be moved higher as society adapts to future temperatures.

For the 311 definition, we project that compound proportion will more than double for 1–3 °C of warming, to compose ~25% of heat wave risk under doubled CO_2; changes are larger for definition parameter values that allow longer breaks or shorter duration compounded events. This suggests that with global warming it is increasingly important to consider vulnerability from prior heat waves when characterizing heat wave risk. Vulnerability from prior heat waves may come from a few different sources:

1. dehydration—when under thermal stress the human body sweats more and can lose water at rates of 1–1.5 L per hour (Coyle, 2004; Packer);

2. building thermal inertia—without A/C, building interior temperature often exceeds and has smaller diurnal cycles than outdoor temperature, and after heat waves its cooling can lag that of the outdoors by a few days (Pyrgou et al., 2017; Ramamurthy et al., 2017; White-Newsome et al., 2012); also those most vulnerable (the elderly and sick) often do not leave buildings or do not have A/C during heat waves (Lane et al., 2013);
3. limited social system capacity—during severe heat waves emergency response time increases due to too many calls, and hospital emergency wards and morgues fill up, struggling to treat patients and process bodies in a timely manner (Keller, 2015; Klinenberg, 2015);
4. power system disruptions— extensive A/C use during heat waves causes excessive electricity demand and resulting outages in pole-top and substation transformers (Aivalioti, 2015); inland bodies of water used for power plant cooling are hotter during and presumably shortly after heat waves causing reduced power plant efficiency (van Vliet et al., 2012);
5. transportation delays—low air density from very high temperatures makes airplanes unable to take off without weight reductions (Coffel et al., 2017), causing disruptions with ripple impacts for days (Wichter, 2017); overheated overhead electric train lines sag and sometimes collapse, causing travel delays and cancelations and sometimes taking days to repair (e.g., Rose).

All these sources of vulnerability are not immediately remedied during a short break of cooler days, making compound days likely more impactful than hot days occurring long after a prior heat wave.

Prior work quantifying such vulnerability is limited. One reason for sparsity of the relevant literature is that temporally compound heat wave events have historically been uncommon (Figure S4), and thus not a significant public health concern. However, the increasing proportion of heat wave hazard from compound days requires that we carefully consider the potentially heightened vulnerability due to prior heat waves. Prior studies of mortality-health relationships provide some insights, as they often examine mortality at different lags from a given temperature day. Mortality often lags cold extremes by many days; in contrast, mortality lags hot extremes not at all or to a maximum of a few days, suggesting that lasting vulnerability for prior heat waves may be limited (Gosling et al., 2009). The source of these lagged relationships cannot be discerned from such statistical analyses. To estimate future compound heat wave risk, and effectively understand whether the impacts of individual heat waves add nonlinearly in time, more targeted work is needed to quantify and understand vulnerability from prior heat waves and the influence of subsequent cool days.

There are many avenues in which people may adapt to the increasing proportion of heat wave hazard from compound heat waves, including improved heat wave warning systems (McGregor et al., 2010), resilient building design and materials (Fisk, 2015), and power and medical system emergency preparedness (Aivalioti, 2015; Bobb et al., 2014; Fouillet et al., 2008). To facilitate such adaptation, we encourage rigorous quantification of the impacts associated with compound days as a topic for future work. A challenge in doing such a study for mortality is the fact that mortality can be displaced by heat waves, meaning that those vulnerable to heat waves perish in an initial heat wave and thus reduce the pool vulnerable to subsequent events (McMichael et al., 2006). This effect might make mortality from compound days lower than that of heat wave days occurring long after prior events. Morbidity (e.g., emergency room visits) or occupational health hazards are less subject to displacement effects and so may relate more clearly to compound days (Fuhrmann et al., 2016).

This work presents a first look at temporally compound heat wave events, leaving various ways this analysis might be refined. Some possible directions include redoing this analysis using a combined temperature-humidity metric such as wet bulb temperature that directly reflects heat stress (McGregor, 2012; Sherwood & Huber, 2010); adding a spatial extent requirement when identifying heat wave events (McKinnon et al., 2016a; Stefanon et al., 2012); using other GCMs, which present a range of projections for changes in temperature extremes and presumably compound heat waves (Gosling et al., 2012; Sillmann et al., 2013a); utilizing a regional climate model with resolution ~1 km over an urban metropolis to see how urban heat island effects influence projected change in compound proportion (e.g., Ramamurthy et al., 2015); and more fully characterizing the relevant components of temperature time series using the Matern statistical models, which allow a wide range of correlation structures (North et al., 2011; Sun et al., 2015).

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