Short Warm-Side Temperature Distribution Tails Drive Hot Spots of Warm Temperature Extreme Increases under Near-Future Warming[Ⓐ]

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ABSTRACT

Regions of shorter-than-Gaussian warm-side temperature anomaly distribution tails are shown to occur in spatially coherent patterns in global reanalysis. Under such conditions, future warming may be manifested in more complex ways than if the underlying distribution were close to Gaussian. For example, under a uniform warm shift, the simplest prototype for future warming, a location with a short tail would experience a greater increase in extreme warm exceedances relative to a fixed threshold compared to if the distribution were Gaussian. The associated societal and environmental impacts make realistic representation of these short tails an important target for climate models. Global evaluation of the ability for a suite of global climate models (GCMs) contributing to phase 5 of the Coupled Model Intercomparison Project (CMIP5) suggests that most models approximately capture the principal observed coherent regions of short tails. This suggests the underlying dynamics and physics occur on scales resolved by the models, and helps build confidence in model simulations of extremes. Furthermore, most GCMs show more rapid future increases in exceedances of the historical 95th percentile in regions exhibiting short tails in the historical climate. These regions, where the ratio of exceedances projected by the GCM compared to that expected from a Gaussian sometimes exceeds 1.5, are termed hot spots. Prominent hot spots include western North America, Central America, a broad swath of northwestern Eurasia, and the Indochina Peninsula during boreal winter. During boreal summer, central and western Australia, parts of southern Africa, and portions of central South America are major hot spots.

1. Introduction

Extreme warm temperatures are associated with a multitude of negative impacts on society and the environment. Extreme heat is often associated with human suffering (Anderson and Bell 2009), wildfires (Dole et al. 2011; Abatzoglou and Williams 2016), increased energy demand, poor air quality (Jacob and Winner 2009), and damage to ecological and agricultural productivity

(Ciais et al. 2005). Several high-profile extreme heat events have occurred in the recent past, demonstrating the dangerous capacity of such phenomena. For example, in 2003 a heat wave over western Europe was associated with up to 70 000 excess fatalities (Robine et al. 2007). Other notable heat events over the last few decades include those in Chicago, Illinois, in 1995 (Karl and Knight 1997); Russia in 2010 (Dole et al. 2011); Europe in 2015 (Dong et al. 2016); and India in 2015 (Wehner et al. 2016). Furthermore, extreme heat is projected to increase in frequency and severity under future global warming (Kirtman et al. 2013).

Observed increases in the frequency and severity of extreme heat have been documented over the last several decades both at global and regional scales (Alexander

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et al. 2006; Perkins et al. 2012; Bador et al. 2016; Donat et al. 2016; Horton et al. 2016). In some regions, record warm temperature exceedances have been documented to be far outpacing record cold exceedances (Meehl et al. 2009; Rowe and Derry 2012). These trends can be attributed to anthropogenic greenhouse forcing in many cases (Morak et al. 2013; Fischer and Knutti 2015; Diffenbaugh et al. 2017) and are consistent with expectations of future warming as projected by climate models (Coumou and Robinson 2013; Wuebbles et al. 2014; Russo et al. 2014; Sillmann et al. 2013). Projected changes carry substantial implications for society and the environment with many regions projected to experience extreme heat with a frequency and severity unprecedented in the current climate. In some particularly severe cases, warming could potentially lead to temperatures exceeding thresholds that are beyond human survivability when combined with high humidity (Sherwood and Huber 2010; Im et al. 2017). It is therefore critical to gain a thorough understanding of the rate at which these changes are likely to occur and to identify regions that may be more susceptible to large increases in dangerous extreme warm threshold exceedances in the near future.

Marked departures from Gaussianity in temperature probability distribution functions (PDFs) have been well documented in observations (Cavanaugh and Shen 2014) and reanalyses (Perron and Sura 2013; Loikith et al. 2013). In many cases, non-Gaussian PDFs are found in spatially coherent regions suggesting a prominent role for large-scale climatological forcing (Stefanova et al. 2013; Garfinkel and Harnik 2017). In the case of a non-normal temperature PDF, future changes in extreme temperatures may be manifested in more complex ways than if the distribution were Gaussian (Sardeshmukh et al. 2015; Guirguis et al. 2017). For example, under a uniform warm shift across the PDF, the simplest prototype for future warming, a PDF with a longer-than-Gaussian warm-side tail would experience smaller increases in extreme warm temperature threshold exceedances than if the distribution were Gaussian (Ruff and Neelin 2012). Long tails are of interest since they indicate a climate that receives rare but very large excursions from the mean; however, a shorter-than-Gaussian tail would lead to more rapid increases in extreme warm temperature threshold exceedances under the same uniform shift than either a Gaussian or long-tailed PDF (Loikith and Neelin 2015). Figure 1 illustrates the influence of non-Gaussian versus Gaussian tails on changes in the frequency of extreme warm temperature threshold exceedances.

While future warming may not be manifested as a simple uniform warm shift to the PDF in all cases, evidence from several studies suggests this is a reasonable first approximation for most observed (Ballester et al.

FIG. 1. The effect of non-Gaussian warm and cold tails on changes in extreme temperature exceedances relative to a fixed threshold under a uniform warm shift. The red- and blue-shaded areas represent exceedances of fixed warm and cold temperature thresholds, respectively. The solid curve is the preshifted probability distribution and the dashed curve is the same distribution after a uniform warm (rightward) shift. The yellow vertical lines are the preshifted (solid) and postshifted (dashed) distribution means. Examples are for (top) a Gaussian, (middle) a short warm-tailed distribution, and (bottom) a long warm-tailed distribution.

2010; McKinnon et al. 2016; Rhines and Huybers 2013; Weaver et al. 2014) and projected (Lau and Nath 2012) changes in extremes. However, some changes to higher moments of the PDF have been documented (McKinnon et al. 2016; Cavanaugh and Shen 2014; Donat and Alexander 2012) and nonlinearities in the interaction between changes in the mean and extremes under conditions of nonnormality may result in more complex changes to extreme exceedances under even a simple shift prototype (Huybers et al. 2014). Additionally, land-atmosphere coupling under a warming climate will likely

cause extremes to change at a different rate than the mean in some regions resulting in complex interactions between warming and PDF shape (e.g., Fischer et al. 2007; Seneviratne et al. 2010; Berg et al. 2014; Donat et al. 2017).

The combination of the existing evidence of non-Gaussian behavior in near-surface temperature PDFs combined with the demonstrated potential impacts of this distribution morphology makes it an important topic of study for more confidently projecting future changes in extremes. Shorter-than-Gaussian warm-side tails, due to their potential to substantially impact the magnitude and rate of change in extreme warm temperature exceedances under even modest warming, are a special case of nonnormality due to the potentially large associated impacts. It is therefore important for climate models to realistically capture short warm-side tails in simulations of the historic climate, in order to boost confidence in future projections of changes in warm extremes. Indeed, Borodina et al. (2017) demonstrate that variability in climate model fidelity at simulating temperature PDF shape is a major source of uncertainty in future projections of warm temperature extremes in some regions. Furthermore, quantifying the extent to which short-tail regions in the current climate are an indicator of a more rapid increase in the number of extreme warm threshold exceedances under simulated warming would highlight regions of particular vulnerability to large increases in extreme heat in the near future. Loikith and Neelin (2015) documented coherent regions of shorter-than-Gaussian PDF warm-side tails over North America in boreal winter and summer, suggesting potentially substantial implications for future changes in heat extremes. Building on this work, we evaluate the fidelity with which a large suite of global climate models (GCMs) reproduces observed short warm-side tails in simulations of the historical climate. We further investigate projected changes in regions of short tails to assess the effect these special cases of PDF shape have on simulated future warming.

2. Data

Reference data for daily 2-m temperature are from the Wang and Zeng (2014a,b) suite of global land (excluding Antarctica) datasets. We employ the product combining NASA's Modern Era-Retrospective Analysis for Research and Applications reanalysis (Rienecker et al. 2011) with the Climatic Research Unit 3.10 (Mitchell and Jones 2005) gridded monthly 2-m temperature observations. Details on the construction and validation of this merged dataset can be found in Wang and Zeng (2013). Data are originally provided at hourly temporal resolution, which we average to make daily

means. The combination of the reanalysis with gridded station data reduces the observational uncertainty compared to traditional reanalysis, and several studies have evaluated the quality of this dataset across various regions of the world finding generally reasonable agreement with other observing platforms (e.g., Wang and Zeng 2013; Wang and Zeng 2014a,b; Wang and Zeng 2015; Loikith and Neelin 2015; Loikith et al. 2015a,b).

GCM data are from phase 5 of the Coupled Model Intercomparison Project (CMIP5; Taylor et al. 2012). When more than one ensemble member is available for a given GCM, only the first run for that model is considered. Model evaluation is performed using the simulation of the historical record provided by each GCM while future projection analysis is performed for the representative concentration pathway 8.5 (RCP8.5) scenario simulations that assume a business as usual (minimal mitigation) evolution of emissions of climate relevant constituents. We employ all GCMs with available data for daily temperature for both the historical and RCP8.5 experiments, resulting in a total of 29 individual models spanning a wide range of horizontal resolutions (see Table S1 in the online supplemental material for this paper).

3. Methodology

All analyses are performed over 27-yr periods. This record length is used to maximize the overlap period of the reanalysis with the historical CMIP5 simulations, which spans 1979–2005. Future projection analysis is also performed over 27-yr periods so that sample sizes are consistent when assessing extreme warm temperature exceedances. Temperature anomalies are computed by subtracting the daily climatology of the historical period, computed as the average value for each day over the 1979–2005 period, from each day. The climatology is computed separately for each CMIP5 model and for the reanalysis such that anomalies are always relative to the climatology of the dataset. For the historical period, the linear trend is removed from all anomaly time series at each grid point, separately for each season. Anomalies of future projections are also relative to the historical period climatology so as to measure warming magnitude relative to the historical base climatology. Analysis is performed over two 3-month seasons, December–February (DJF) and June–August (JJA), to capture summer and winter in both hemispheres. Therefore, we compute anomalies for, remove linear trends from, and estimate standard deviations from time series consisting of a total of 2430 and 2482 days for DJF and JJA, respectively. For computing the multimodel ensemble mean, all data are first interpolated onto a common $2^\circ \times 2^\circ$ latitude–longitude grid.

Following [Loikith and Neelin \(2015\)](#), non-Gaussian temperature PDF warm-side tails are identified at each grid point using the following process. First, the 95th percentile of the daily temperature anomaly PDF is computed. The PDF is then shifted uniformly by 0.5 standard deviations (σ). A shift in σ is chosen over a standard value (1° for example) so that the shift magnitude is proportional to the width of the PDF. If the percent of days exceeding the unshifted 95th percentile is significantly greater or less than that expected from shifting a Gaussian by 0.5σ , the tail is deemed shorter or longer than Gaussian, respectively. Significance is measured by applying this shift procedure to a randomly generated Gaussian of length equal to the data 10 000 times to create a distribution of the exceedance values that could be obtained by this sampling of a Gaussian. If the actual percent of days exceeding the 95th percentile of the unshifted temperature PDF is greater than the 95th or less than the 5th percentile of the distribution of the synthetic Gaussian shift exceedance, the warm tail of that grid point is deemed significantly non-Gaussian. For the time series length here, the 5th and 95th percentile significance thresholds of the randomly sampled distribution are 12% and 14% (rounded to the nearest integer) of days exceeding the preshifted 95th percentile, respectively. This procedure for measuring non-Gaussianity has a practical application in that it highlights the potential influence non-Gaussian tails can have on future exceedances of extreme warm temperatures under the simple case of a uniform warm shift while also being a variant of the Kolmogorov–Smirnov/Lilliefors test for normality [see [Loikith and Neelin \(2015\)](#) for additional details]. It also specifically targets the departure from Gaussianity in the warm tail only without influence from asymmetry at other parts of the distribution as would occur if skewness were used. However, short tails are very often coincident with negative skewness, although the most negatively skewed distributions do not always have the shortest warm-side tails. Therefore at least in a qualitative sense, negatively skewed temperature distributions can be considered indicators of shorter-than-Gaussian warm-side tails in most cases. To evaluate the ability of the CMIP5 models to simulate short tails from reanalysis, the shift procedure is applied to the CMIP5 models using each model's own historical 95th percentile of the temperature anomaly distribution.

4. Results

a. Short tails in reanalysis

[Figure 2](#) shows regions of non-Gaussian warm-side tails computed from the reanalysis over the years 1979–2005. Specifically, the shaded values in [Fig. 2](#) are the

ratio of the percent of days exceeding the preshifted 95th percentile of the temperature PDF after a 0.5σ shift to the percent expected if the PDF were Gaussian and shifted by 0.5σ (which would give 13%). This metric is referred to as the shift ratio herein. Grid cells shaded in red and blue, as well as those unshaded, indicate warm tails that are significantly shorter, longer, and indistinguishable from a Gaussian, respectively. In this study we focus on the shorter-than-Gaussian tails. The same shift ratio is computed for in situ station data, where data are available, for the same time period used in the reanalysis. Results are shown in [Fig. S1](#) in the supplemental material for qualitative comparison and they largely agree with the reanalysis results in [Fig. 2](#) where station data exist.

For DJF ([Fig. 2a](#)), several spatially coherent regions of short warm-side tails are evident on each continent. The most notable include a band extending from southwestern Alaska through the north-central United States, which then extends southward into Central America, a broad area across eastern Europe extending into central Asia, a portion of southeast Asia, much of interior Australia, southern and central Africa, and interior subtropical South America. In JJA, the spatial extent and magnitude of the shift ratio for short warm-side tails is less notable in the Northern Hemisphere, as compared with DJF. However, notable short-tail regions in JJA include strong bands in central South America and southern Africa, parts of northwest Africa (away from the coasts), and portions of the eastern United States. The large ratio values found in these regions indicate that under the simple warming paradigm of a uniform rightward shift in the PDF, a much greater number of days would exceed the 95th percentile of the preshifted climate, in some cases by as much as 1.5–2 times that expected if the distribution were Gaussian.

This apparent seasonality in the coverage and magnitude of short tails may indicate that horizontal temperature advection, which is generally strongest in the more baroclinic midlatitude winter environment, is an important factor in determining departures from Gaussian. Additionally, the spatial coherence and generally large scale of these short-tailed regions suggests an influence from large-scale meteorological dynamics. Land–atmosphere interaction likely also plays a role in some regions for both seasons. For example, in a typically snow-covered area, when the temperature approaches 0°C , excess heat may be expended from melting snow, leading to a limit on warm-tail length. In climatologically dry and cloud-free areas, most or all solar energy is converted to sensible heat affecting the warm-tail properties ([Fischer and Schär 2009](#); [Cattiaux et al. 2015](#)). In some cases, proximity to a moderating influence such as a large body

FIG. 2. Shift ratio (i.e., the ratio of the percent of days exceeding the preshifted 95th percentile of the actual distribution after a 0.5σ uniform warm shift to the percent expected if the distribution were Gaussian) for (top) DJF and (bottom) JJA. Values greater than 1 indicate a shorter-than-Gaussian warm-side temperature PDF tail. White areas over land are where the warm-side tail is not significantly distinguishable from a Gaussian at the 5% level. Results are for the period 1979–2005 for the MERRA-CRU reanalysis. Stars identify where scatterplots are produced in Figs. 4 and 5.

of water may curtail large warm excursions. For example, the prevalence of short tails along coastal Alaska and British Columbia in DJF may be due in part to the nearby North Pacific Ocean acting to limit the magnitude of extreme warm events. This would not, however, explain the inland portions of this coherent area of short tails. Some of the tropical regions may plausibly have influences related to precipitation processes and cloud cover, although there is not an immediately clear relationship to patterns of convective zones.

b. Evaluation of CMIP5 historical simulations

1) DECEMBER–FEBRUARY

Figure 3 shows the DJF shift ratios for each of the 29 CMIP5 GCMs and the multimodel ensemble mean (MMEM), computed in the same manner as for the

reanalysis in Fig. 2. Models are ordered alphabetically with the MMEM as the last panel. The MMEM is computed by averaging the shift ratios of all 29 GCMs. Individual ensemble members are presented on their native grids while the MMEM is on a common 2° latitude–longitude grid mesh. The pattern correlation between the shift ratio for each model and the reanalysis is shown in the bottom left of each panel. The generally good pattern correlations indicate that most models and the MMEM resemble reanalysis to a reasonable degree, globally. Furthermore, in general, the MMEM captures many of the principal patterns of short tails identified in the reanalysis. This reasonable agreement is despite the MMEM being on a grid that is 4 times as coarse as the reanalysis. For example, the band of notably short warm tails over North America, with ratio values exceeding 1.7 in some places, is clearly reproduced by the MMEM.

FIG. 3. DJF shift ratios for the 29 CMIP5 models and (bottom right) the CMIP5 multimodel ensemble mean. Values greater than 1 indicate a shorter-than-Gaussian warm-side temperature PDF tail. White areas over land are where the warm-side tail is not significantly distinguishable from a Gaussian. Results are for the period 1979–2005. The numbers at the bottom left of each panel are the pattern correlation computed between the model and MERRA-CRU. Pattern correlation values are computed using the regridded model and MERRA-CRU fields.

This is also the case for the Eurasian region, with the MMEM even capturing the band of shortest tails, which extends southeast from the Baltic Sea. The MMEM also realizes many of the smaller areas of short tails such as over Australia, central Africa, the Caribbean and Gulf of Mexico coasts, and Central America.

In some regions of short tails, the MMEM does not resemble the reanalysis as closely as the above examples. This is the case for southern Africa and central South America, where there is some disagreement with the magnitude and spatial extent of the short tails. However, the overall strong resemblance between the

MMEM and the reanalysis suggests that the CMIP5 suite of GCMs is capable of resolving and reproducing the key physical mechanisms driving these spatially coherent regions of short warm-side tails.

While the MMEM shows mostly strong agreement with reanalysis, some intraensemble variability is evident in Fig. 3. For example, every model has some variant on the North American short-tail regions; however, some models such as the fourth-generation INMCM4, NorESM1-M, and BNU-ESM exhibit shift ratios that are much greater over a larger area than in the reanalysis. In other cases, such as ACCESS1.0, EC-EARTH, CMCC-CM,

FIG. 3. (Continued)

and HadGEM2-AO, the same region has lower ratio values and in some cases the spatial extent of the short-tail regions is smaller than in the reanalysis. Using the transition between predominantly short tails to long tails over North America, which extends from central Alaska southeastward to the Great Lakes, as a measure for model agreement shows that while all models capture some form of this transition, many models have this boundary misplaced compared with the reanalysis. Despite this variability in model agreement, the plurality of models capturing this transition suggests they are capable of simulating the key mechanisms and physics driving this feature.

Similar results are found for the Eurasian and Australian short-tailed regions. All models produce short tails across this region; however, disagreement in the

extent and magnitude of the short tails is common. For example, IPSL-CM5A-MR has an elongated band of very high ratio values stretching from Scandinavia to central Asia, while MIROC5 does not capture this area of maximum short tails. Some models do not produce a large enough area of short tails such as for MIROC-ESM-CHEM and IPSL-CM5B-LR. Over Australia most of the CMIP5 models capture short tails with reasonable fidelity while some models have a more extensive area of short tails compared with the reanalysis.

Skill across the CMIP5 suite is less robust for other areas of short tails. For example, few models produce a region of short tails over South America that resembles that from the reanalysis. Those that do show short tails over South America, such as CMCC-CM, do not

FIG. 4. As in Fig. 3, but for JJA.

capture the reanalysis spatial pattern. Many models do capture the band of short tails across central Africa, the southern Arabian Peninsula, and far southeastern Asia. It should be noted that the number of observations contributing to the reanalysis over some of these regions is limited, and therefore it may be prudent to exercise caution in interpreting the details of the model comparisons with reanalysis in such cases without further assessment of observational uncertainty.

2) JUNE–AUGUST

Figure 4 shows the CMIP5 model ratio values for JJA in the same format as Fig. 3 for DJF. The MMEM shown at the bottom right exhibits several examples of

reasonable agreement with reanalysis for short-tail regions. However, compared with the model agreement with reanalysis for DJF, the models show an overall lower pattern correlation during JJA. While this indicates lower model skill at capturing short warm tails at the global scale in JJA compared with DJF, several of the individual principal short-tail regions are reproduced by the models and the MMEM, although with varying degrees of agreement. Over South America, the MMEM shows short tails extending farther north and west than in the reanalysis while the area of high ratio values in the central portion of the continent shows reduced magnitude. Interestingly, the narrow band of short tails that follows the Andes from the main region of short tails south to southern Chile is evident in the

FIG. 4. (Continued)

relatively coarse-resolution MMEM. The MMEM also captures the shape, extent, and magnitude of the short-tail region in southern Africa. The relatively small areas of short tails across northern Australia and over Papua New Guinea are also captured by the MMEM.

In the Northern Hemisphere, where regions of short tails are generally closer to Gaussian and occur in less spatially coherent regions than in the Southern Hemisphere, the MMEM is still able to capture some of the features found in the reanalysis. For example, the MMEM shows a similarly shaped area of short tails in the western United States with similar agreement over northern Canada along the Arctic coast. However, the MMEM does not reproduce the area of short tails over the eastern United States that forms a coherent feature in the reanalysis. Along the Mediterranean coast of

Europe, the MMEM and reanalysis both show short tails despite the relatively small spatial scale of this region. Across Asia, many of the statistically significant areas of short tails are also captured by the MMEM, even when they are relatively small in spatial extent. For example, the regions of short tails over eastern Russia into northeast China are broadly reproduced by the MMEM, as are regions in central Asia. These examples are a confidence booster in the ability of the suite of CMIP5 GCMs to capture important physical and dynamical mechanisms associated with temperature variability and suggest high resolution is not necessarily essential to capturing even the smaller regions of short tails.

While the MMEM generally matches the reanalysis well, there is considerable variability across the 29-model suite. For example, many models capture the general

spatial extent and magnitude of the South American short-tail region well while others miss the feature entirely. Examples of well-performing models for this region include MPI-ESM-MR, CNRM-CM5, and CMCC-CM5. On the other hand, INMCM4, CanESM2, and CMCC-CESM miss this region. The ACCESS1.0 and HadGEM models show an area of very short tails across the northwestern portion of South America, which contributes to the northwestward extension of the short-tail region in the MMEM, compared with the reanalysis. Similar variability can be seen across the short-tail regions discussed in the MMEM above, with especially strong intraensemble skill variability for the Northern Hemisphere regions.

c. Future projections of change

1) INDIVIDUAL CASES

Projected changes in extreme warm temperature threshold exceedances are investigated for 12 grid cells located within notable areas of short warm-side tails across the globe (Figs. 5 and 6). In these figures, all data have been regridded onto a common 2° latitude–longitude grid mesh and display the percent of days exceeding the historical 95th percentile for the simulated mean warming for each CMIP5 model. A model is said to agree with the reanalysis if its historical 0.5σ shift ratio is greater than half the distance between the 5th percentile of the observational uncertainty and the 95th percentile of the Gaussian uncertainty lines (see Fig. 5 caption for more elaboration). This range is shown with horizontal gray lines and aims to provide a qualitative constraint on the model projections (e.g., how do projections differ across model performance?). If a model had perfect agreement with the reanalysis, the uniform 0.5σ warm shift value in Table S2 in the supplemental material would result in the exceedance percentage delineated with the dashed gray line. We note that in examples with very short warm tails, the range of model shift percentages that is considered to be in good agreement with the reanalysis is broader since the distance between the reanalysis and the Gaussian shift curves is larger. However, in these cases, a model could have a shift percentage a few points below the reanalysis and still be considerably non-Gaussian whereas in cases where the warm tail is not as short, a similar distance below the reanalysis could render the model PDF statistically indistinguishable from a Gaussian. We therefore feel this a reasonable discriminator for model evaluation. Once a location has exceeded 1σ of warming, a large proportion of the PDF is to the right of the historical 95th percentile, rendering the shape of the tail less important to changes in exceedances and thus data above that threshold are not shown.

Two questions can be posed that Figs. 5 and 6 help shed light on. First, in places with non-Gaussian short warm tails, are projected changes in warm threshold exceedances greater than would be expected from shifting a Gaussian by the same mean warming? Second, does the model skill at capturing non-Gaussian tails influence future projections of exceedances? For the DJF grid cells (Fig. 5) model performance at qualitatively reproducing non-Gaussian warm-side tails in the historical simulations is generally good, as highlighted by the number of symbols without a black background, with the most disagreement at the Arabian Peninsula and Australian grid points. In most cases, models that demonstrate weak skill at reproducing short tails do so in the lower (not as short warm tail) direction, although some models exhibit substantially shorter tails than the reanalysis at the British Columbia and Florida grid cells (Fig. S2). In all six regions, the plurality of models shows greater-than-Gaussian threshold exceedances in future projections, especially for models with good short-tail agreement. This supports the hypothesis that short tails in the historical simulation do result in more-rapid-than-Gaussian increases in extreme warm temperature days in many cases in the near future.

The degree to which models follow the shift prototype curves from the reanalysis varies. This is partly associated with differences in the model PDF shape in the historical simulation. For instance, in the Arabian Peninsula and Australia, models with weak agreement all have closer to Gaussian tails in historical simulations than the reanalysis and tend to more closely follow the Gaussian shift curve. The Florida grid point, with the highest agreement among the models, consistently shows projections conforming closely to changes expected from a shift in the reanalysis distribution. For other regions, the change in exceedances is larger than that expected from Gaussian to varying degrees, but not always by as much as would be expected by a simple shift of the reanalysis. This would partly be due to some degree of PDF morphology change that is more complex than a simple shift. Overall, there is strong indication that the degree of tail shortness is proportional to the future projected exceedances.

Figure 6 shows results for JJA in the same format as Fig. 5. As explained above, the smaller departures from Gaussian in some JJA examples do inherently make the window of model agreement smaller, which could contribute to the overall larger number of models that do not pass the threshold of strong agreement with the reanalysis. However, this is notably not the case for southern Africa and central South America where there is considerable model disagreement despite the reanalysis showing very short tails. In general, a considerable number of models do not exhibit strong agreement with the reanalysis at any of the grid points in Fig. 6, with many examples of models

FIG. 5. Scatterplots of shift magnitude vs percent of days exceeding the historical 95th percentile for six select locations displayed with stars in Fig. 2a. All results are for DJF. The warming magnitude in standard deviations is along the x axis and the percent of days exceeding the 95th percentile of the historic or unshifted PDF is along the y axis. The thick gray curve displays the exceedances per shift magnitude for the reanalysis. The thin gray curves delineate the observational uncertainty at the 5th and 95th percentiles computed by randomly selecting half of the temperature anomalies at the grid cell and shifting the sampled PDF by 0.5σ 10 000 times. The thick black line is the expected exceedances per shift magnitude for a Gaussian with the thin black lines delineating the significance bounds for a Gaussian tail at the 5th and 95th percentiles. The solid horizontal gray lines delineate the bounds used to determine model agreement with observations and the dashed gray line is the exceedance percentage for a 0.5σ uniform warm shift across the reanalysis PDF. Each CMIP5 model is indicated by a color. The circles, crosses, and $\times$ s correspond to warming averaged over 2006–32, 2039–65, and 2074–2100, respectively. Black circles and squares around a symbol indicate that the model does not validate well against the reanalysis and has a shorter and longer warm-side tail than the reanalysis, respectively (see Table S2).

FIG. 6. As in Fig. 5, but for JJA and different locations.

that are not statistically distinguishable from a Gaussian or that may even have longer-than-Gaussian tails (Fig. S2 for details). However, for those models that do capture short tails that resemble the reanalysis, future projections are generally for more-rapid-than-Gaussian increases in extreme warm threshold exceedances, especially for the mid-twenty-first century. This is notably apparent for central South America and southern Brazil. While the

Great Basin grid cell is barely shorter than Gaussian, most models capture this characteristic and show projected warming that is greater than Gaussian for those models with a smaller than 1σ projected warming by midcentury.

In general, Figs. 5 and 6 show that models that capture short warm-side tails do project more-rapid-than-Gaussian increases in extreme warm threshold exceedances. Furthermore, model skill does have a substantial influence on

the behavior of projected threshold exceedances, providing some constraint for interpreting future projections at these locations where models do not reasonably simulate short tails. Specifically, models with tails that are closer to Gaussian compared with reanalysis tend to project warming that is also similar to that expected from shifting a Gaussian. In some cases, such as over South America, uncertainty associated with the reanalysis may call into question the reliability of the identification of short tails; however, the robust spatial coherence of the short-tailed regions suggests the short tails are a result of a larger-scale physical or dynamical process, which boosts confidence in the results.

2) GLOBAL HOT SPOTS OF WARMING

Regions where projected changes in exceedances are much greater than would be expected from shifting a Gaussian distribution by the simulated warming are termed hot spots. To identify hot spots and assess the influence short warm-side tails in the historical period have on their occurrence under warming, we compute the ratio of the percent of days exceeding the historical 95th percentile to the percent of days that would exceed the historical 95th percentile if the distribution were Gaussian. This procedure is performed at each grid cell using the period 2039–64 and presented in similar fashion to Figs. 3 and 4 in Figs. 7 and 8. To focus on the influence of non-Gaussian warm-side tails, only areas that exhibit statistically significant non-Gaussian warm-side tails in the historic climate are shaded (as in Figs. 3 and 4). Additionally, any grid cell where the mean warming is greater than 1σ , as is common in lower latitudes, is not shaded. In these places, the effect of low variance supersedes the influence from non-Gaussian tails on rapid increases in extreme warm exceedances under midcentury projected warming. This effect has been previously documented (e.g., Fischer and Knutti 2015; Fischer et al. 2012).

Notable hot spots in DJF (Fig. 7) are found over western North America, Central America, a broad swath of Eurasia, the Indochina Peninsula, and much of Australia in the MMEM. Parts of La Plata basin of South America, southern Africa, tropical Africa, and portions of the Arabian Peninsula also exhibit coherent regions of larger-than-Gaussian exceedances although with lower ratio values than the abovementioned hot spots. All hot spots are coincident with notable regions of short warm-side tails in the reanalysis and MME of the CMIP5 historical climate analysis. Indeed, even the shapes of the greater-than-Gaussian future exceedance regions as projected by the models closely match the regions of short tails in the historical MMEM, which validated well against the reanalysis. While there are some differences in the magnitude of the ratios between

the MMEMs in Figs. 3 and 7, such as along western Canada and eastern Europe, the principal patterns match exceptionally closely. This strongly suggests that regions with shorter-than-Gaussian warm-side temperature PDF tails are likely to see more rapid, and in some cases much more rapid, increases in the number of days exceeding extreme warm temperature thresholds by the mid-twenty-first century.

The individual ensemble members are also presented as a way of gauging intraensemble variability, to assess the influence model representation of historic short tails on future exceedances, and to highlight where warming exceeds 1σ . For example, all models produce an area of greater-than-Gaussian increases in exceedances over a wide swath of central and western North America. This feature is stronger and more coherent in some models, such as IPSL-CM5A-LR, CESM1(BGC), and CCSM4, than others, such as CMCC-CMS, IPSL-CM5B-LR, HadGEM2-AO, and MIROC5. The magnitude of the future projection exceedance ratios does not always correspond to how the model produced short tails in the historical record, although in many cases the models with the most robust short tails also show the most non-Gaussian warming behavior in the future.

For the large Eurasian hot spot, there is more apparent variability across the suite in the magnitude, extent, and morphology of the hot spot and the connection between the model historical short-tail representation and the future projected exceedance ratios. However, every ensemble member projects more-rapid-than-Gaussian increases in extreme warm exceedances across central Asia and most of Europe. Some models do not project strongly non-Gaussian warming over the portion of the Eurasian short-tailed region with the shortest tails, namely the band stretching from Scandinavia southeastward into central Russia, suggesting a fundamental change in PDF shape in this region as opposed to the maintenance of a short tail. This is consistent with the western Russia example in Fig. 5, which showed strong model agreement but with projected exceedances lying partway between changes in exceedances expected from Gaussian and those that the simple shift prototype would predict.

For JJA (Fig. 8), the MMEM also shows more-rapid-than-Gaussian warming in many short-tail regions, most notably over central South America, northern Australia, southern Africa, and many regions of Asia and North America. As in DJF, most of these regions exhibit short tails in the reanalysis and model simulations of the observational period. In the Northern Hemisphere, many of these hot spots occur in regions that are climatologically very hot, indicating a near-term projection of rapid increases in very extreme summer temperatures with potentially large impacts. The individual ensemble members

FIG. 7. Ratio of percent of days projected to exceed the historical 95th percentile to that expected if the distribution were Gaussian. Values are computed over the period 2039–65 of the RCP8.5 scenarios for the CMIP5 models for DJF. Only areas that have significant non-Gaussian tails that the historical climate simulate for each model are shaded. If the projected warming averaged over the 27-yr period is greater than 1σ , the grid cell is also unshaded (since tail differences are less important for large shifts). The multimodel ensemble mean of the ratio values is shown at bottom right. Values greater than one are where the projected increase in exceedances is greater than expected if the distribution were Gaussian.

show that for many of the lower-latitude short-tail regions, projected warming is greater than 1σ , with considerable variability in how much land surpasses this level of warming. However, there is consistency across the suite of more-rapid-than-Gaussian warming in many of the hot spots that are clearly indicated in the MMEM.

5. Summary and discussion

Results from this study indicate that shorter-than-Gaussian warm-side tails of temperature anomaly

distributions are common globally, occurring in spatially coherent regions, and are important indicators of regions that will likely experience rapid increases in extreme warm temperature exceedances in the near future. Climate model projections of the mid-twenty-first century (2039–65) indicate that most regions that exhibit short tails in the current climate will see larger, and in some cases much larger, increases in the number of extreme warm threshold exceedances than regions with Gaussian or longer-than-Gaussian tails. In general, the CMIP5 models are capable of reproducing short tails

FIG. 7. (Continued)

in these hot spot regions, boosting confidence in the validity of the projections of more-rapid-than-Gaussian change. However, some intraensemble variability in model skill is evident with several factors possibly contributing to model bias. For example, [Donat et al. \(2017\)](#) suggest that the CMIP5 models may be challenged at handling the interaction between soil moisture and extreme heat, which would be particularly acute during summer months in areas where land–atmosphere feedbacks are key for the occurrence of warm extremes. During winter, extremes are more likely to be driven by large-scale advection and dynamical processes, which based on regional-scale evaluation studies (e.g., [Loikith and Broccoli 2015](#); [Lau and Nath 2012](#); [Lau and Nath 2014](#); [Krueger et al. 2015](#)) may be more reliably simulated

in climate models than the physical processes associated with extreme warmth in the summer. Given the demonstrated importance that short tails have on future warming, using model evaluation of shorts tails could provide potential for regionally specific constraint on extreme temperature frequency projection uncertainty (e.g., [Borodina et al. 2017](#)).

Major hot spots, where the percent of days exceeding the historical 95th percentile is sometimes greater than 1.5 times that expected from a Gaussian by midcentury, are found globally and tend to be present more robustly in winter than summer. Winter hot spots include large portions of western and northwestern North America, Central America, a large swath of Eurasia, central South America, southern Africa, and northern Australia. In

FIG. 8. As in Fig. 7, but for JJA.

summer, the ratio of exceedances projected to that expected from a Gaussian tends to be closer to one; however, notable coherent areas of more-rapid-than-Gaussian increases in warm extremes include portions of interior North America, the Arctic coast of Alaska and northwestern Canada, a portion of subtropical Africa north of the equator, the southern Arabian Peninsula, and large swaths of Eurasia. Every one of these hot spots coincides with shorter-than-Gaussian warm-side tails in the current climate, confirming this special case of PDF shape as an indicator of the magnitude and rate of future increases in extreme heat.

These results carry potentially large implications for impacts in many of these regions. While the most robust hot spots are all present in winter, rapid increases in

warm exceedances may bring substantial impacts to ecosystems adapted to cool conditions and that may not have tolerance for heat events. In other places, such as western North America, where winter snowfall provides the majority of the summer water supply and where temperatures are often marginally cold enough for snow, a small warming could result in a large portion of winter precipitation falling as rain.

In other cases, short tails are present in the summer when extreme heat is most common and severe. For example, over interior Australia in summer, short tails are likely to lead to rapid increases in extreme heat in an already extremely hot region. While not reaching the “hot spot” threshold, many portions of North America, Asia, the Arabian Peninsula and northern Africa are

FIG. 8. (Continued)

projected to see larger-than-Gaussian increases in extreme heat during the boreal summer. Many of these regions are already at the upper limits of human comfort and any rapid increase in extremes, especially if coupled with higher humidity, would result in severe impacts on human health and safety.

Overall, the widespread occurrence of short warm-side tails in the historical climate and their association with rapid-warming hot spots under climate change motivates further study of the mechanisms behind these processes. The reasonable fidelity with which many of the CMIP5 models capture these phenomena in the historical period may be taken as a positive indicator for use of these models in projecting warming behavior. However, the more complex PDFs associated with short

tails suggest the importance of analyzing mechanisms of change that could influence warm extremes beyond a simple shift. Further understanding of the mechanisms that drive the occurrence of short tails in the current and future climate will contribute to our confidence in projected changes in temperature extremes in these regions.

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