Title
How Unexpected Was the 2021 Pacific Northwest Heatwave?

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Key Points:

- Summer temperatures in the Pacific Northwest are positively skewed, so hot extremes are more likely than if the distributions were normal
- Community Earth System Model version 2 (CESM2) can simulate events as extreme as the 2021 Pacific Northwest heatwave at points with similar high-order statistics, but they are rare
- Observations do not indicate that the upper tail is warming more than the mean, but CESM2 projects this behavior for very extreme events

Supporting Information:

Supporting Information may be found in the online version of this article.

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How Unexpected Was the 2021 Pacific Northwest Heatwave?

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Abstract The 2021 Pacific Northwest heatwave featured record-smashing high temperatures, raising questions about whether extremes are changing faster than the mean, and challenging our ability to estimate the probability of the event. Here, we identify and draw on the strong relationship between the climatological higher-order statistics of temperature (skewness and kurtosis) and the magnitude of extreme events to quantify the likelihood of comparable events using a large climate model ensemble (Community Earth System Model version 2 Large Ensemble [CESM2-LE]). In general, CESM2 can simulate temperature anomalies as extreme as those observed in 2021, but they are rare: temperature anomalies that exceed 4.5σ occur with an approximate frequency of one in a hundred thousand years. The historical data does not indicate that the upper tail of temperature is warming faster than the mean; however, future projections for locations with similar climatological moments to the Pacific Northwest do show significant positive trends in the probability of the most extreme events.

Plain Language Summary While the 2021 Pacific Northwest heatwave was reasonably well-forecasted by weather models, it was unexpected by many in the climate community because the high temperatures were so extreme. The event has raised questions about whether the probability of very extreme events is increasing faster than would be expected based on historical warming of average temperatures. Here, we analyze the spread of temperatures around the average, which has increased by 1.5°C since 1960, to provide a rough estimate of the probability of the very extreme event of 2021, and assess whether the probability of extreme heat is changing beyond what is expected from warming of average temperatures. By drawing on climate model simulations from regions that are analogous to the Pacific Northwest, we find that similar events can be simulated by climate models, but that they are very rare: when they occur, they are often the largest event across nearly 10,000 years of data. The climate model also suggests that the most extreme events may increase in probability in the future beyond what would be expected from the average climate change signal, although we do not yet see clear evidence of this in the observations.

1. Introduction

During the last days of June 2021, temperatures in the Pacific Northwest (PNW) soared to record highs, leading to myriad negative impacts including a spike in heat-related emergency department visits (Schramm et al., 2021) and human mortality (Henderson et al., 2022), buckled roads (Griggs, 2021), and increased wildfires (Overland, 2021). The human impacts of the heat wave were likely exacerbated by the fact that the region is known for a moderate climate: many homes do not have air conditioning (Bumbaco et al., 2013), so the temperature in both outdoor and indoor spaces could be high throughout the heat wave.

The proximal, meteorological causes of the heatwave are relatively clear. Around June 20th, a circulation anomaly developed in the western subtropical Pacific due to convection associated with the East Asian monsoon system (Qian et al., 2022). This perturbation seeded a Rossby wave train, which propagated eastward along a midlatitude wave guide, and modified the upper tropospheric winds associated with the wave guide as it progressed. By June 25th, an omega-block had developed over the PNW, which progressed eastward and intensified over the course of the heatwave (Neal et al., 2022; Philip et al., 2021). A cross-Pacific atmospheric river also transported latent heat into the region (Mo et al., 2022). The block caused an extended period of clear skies, increased solar radiation at the surface, and subsidence, all of which increased temperatures. Further, downslope winds from the Cascades and other mountain ranges were reported (Philip et al., 2021), causing additional heating. Similar causal factors have previously been identified for PNW heatwaves in general (Bumbaco et al., 2013; Qian et al., 2022); the difference for this heatwave was with respect to magnitude. The geopotential height anomalies associated with the omega-block were found to exceed those in any prior heatwaves within the period of the

ERA5 record (Philip et al., 2021), and daily maximum temperatures at some locations exceeded prior records by 5–6°C (Overland, 2021; Philip et al., 2021).

The meteorological causal factors for the heatwave occurred on top of a changing mean state due to human influence on the climate system. Summertime daily maximum temperatures in the PNW have increased by 0.24°C per decade since 1960 (based on Berkeley Earth data; Rohde et al., 2013), or about 1.5°C in total over that period. Changes in the mean state alone will increase the probability, intensity, and duration of heat waves (Meehl & Tebaldi, 2004); this shift is a well-understood consequence of climate change. However, the magnitude of the temperatures during the PNW heatwave have raised the question of whether the probability of very extreme events is changing faster than would be predicted by a change in the mean. This hypothesis is not supported by a prior analysis of trends in the 50th and 95th percentiles of station data during peak summer from 1980 to 2015 (McKinnon et al., 2016), but results could differ for the most extreme events, and/or for the early summer period during which the PNW heatwave occurred. Similarly, Philip et al. (2021) did not find evidence of dynamical changes in climate models that would lead to increased probability of very hot extremes, but intriguingly also found that a nonstationary generalized extreme value (GEV) distribution fit to data through 2020 (i.e., not including the 2021 event) predicted that the probability of the 2021 event was zero (Philip et al., 2021). Could this result suggest that the 2021 event was truly drawn from a different distribution?

Although the PNW region is associated in the popular imagination as a region of mild climate, it is notable that the region does experience high temperatures during the summertime. For example, between 1901 and 2009, stations in the western half of Washington and Oregon recorded 12 events during which daily maximum temperature anomalies exceeded 10°C (actual temperatures between 28.5°C and 40°C, depending on the location), with no significant trend in the frequency, magnitude, or duration of extreme events over this period (Bumbaco et al., 2013). This behavior—generally mild climate with occasional large positive extremes—is linked to the positive skewness of summer daily maximum temperatures in the region. Positively skewed distributions, all else being equal, can have a substantially higher probability of very extreme events than a normal distribution (Sardeshmukh et al., 2015).

Here, we aim to answer two questions. First, given the historical climate change signal and distribution of daily maximum temperature anomalies, can we provide an estimate of the probability of the event under the assumption that there is no forced change in daily temperature variability? Second, based on historical trends and projections from a climate model large ensemble, is there evidence that hot extremes are changing in a manner inconsistent with an increase in the mean alone? To do so, we draw upon historical records of temperature, some of which extend back to 1900, and a large ensemble of climate model simulations. Our analysis complements the prescient work of Fischer et al. (2021), which quantified the changing probability of record-breaking heat events in climate models, through our focus on the role of non-normality, and the specific focus on the PNW event.

2. Data and Anomaly Calculation

The study relies on in situ measurements of temperature from weather stations in order to characterize the historical statistics of temperature as well as the 2021 event. Consistent with Philip et al. (2021), we use daily maximum temperatures (Tx) in the analysis; unless otherwise noted, the word "temperature" will refer to Tx. Given that the PNW heatwave occurred at the end of June, in advance of peak summertime (Figure S1 in Supporting Information S1), as well as the strong seasonality in daily temperature statistics and circulation patterns, we limit all of our analyses to the 3-day period of June 15-July 15. We focus on the domain of 43–57°N, 115–123°W (see box in Figure 1), which spans the maximum anomalies of the heatwave.

We use three different sets of in situ data in order to maximize spatial coverage: the Global Historical Climatology Network-Daily (GHCND; Menne et al., 2012), station data archived by Environment Canada (EC; Government of Canada, 2022), and the sub-daily measurements in the Integrated Surface Database (ISD; Smith et al., 2011). For ISD, days without at least 18 temperature measurements are excluded to ensure sufficient sampling to provide a good estimate of Tx. The location of stations from each data set is indicated in Figure S2 of Supporting Information S1. Based on station availability and maximizing record length, we subset to GHCND stations that begin by 1900, EC stations that begin by 1925, and ISD stations that begin by 1973 in the United States and 1977 in Canada. Although the ISD records are much shorter, they provide an important source of data in Canada where GHCND stations are sparse. In all cases, we remove measurements with suspect flags, and do

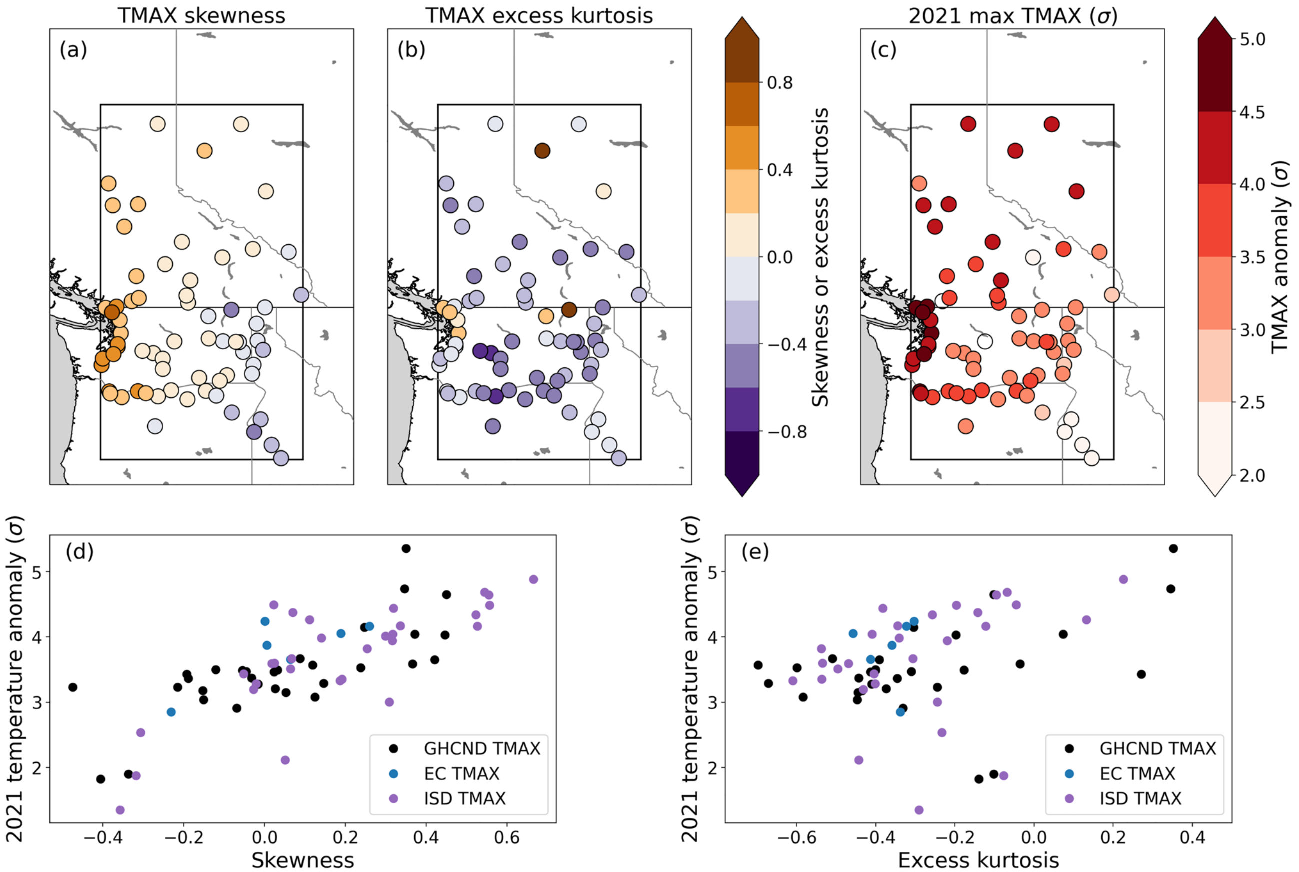

Figure 1. (a) The skewness of maximum temperatures (Tx) at each station. (b) The excess kurtosis of Tx at each station. (c) The maximum temperature anomaly during the 2021 heatwave, measured in standard deviations (σ). (d) The relationship between skewness and maximum standardized 2021 temperature anomalies across stations. (e) The relationship between excess kurtosis and maximum standardized 2021 temperature anomalies across stations.

not include the station if more than 20% of the daily values are missing during the June 15-July 15 period. This yields 32 stations from GHCND, 7 from EC, and 30 from ISD.

Anomalies in the station data are taken with respect to both the seasonal cycle and a simple model for climate change. We model the seasonal cycle with the first five annual harmonics. Both the first annual harmonic and the mean can change linearly with global mean temperature anomalies (GMTA), our proxy for the climate change signal (Hawkins et al., 2020). The GMTA is low-pass filtered using a third-order forward-backward Butterworth filter with a 1/10 year^{-1} frequency cutoff. The remainder of the paper will focus entirely on the temperature anomalies after controlling for the warming of the mean state. Data from 2021 are not used to fit the mean state model, or to calculate the statistics of daily temperature (standard deviation, skewness, kurtosis, and autocorrelation), so that the year can be viewed as "out of sample."

In addition to the station data, we will use daily Tx from the second set of 50 members of the Community Earth System Model version 2 Large Ensemble (CESM2-LE) (Danabasoglu et al., 2020; Rodgers et al., 2021). In contrast to the first 50 members, these members use a smoothed biomass burning forcing data set to reduce discontinuities before 1997 and after 2014, and also incorporate two sets of bug corrections related to aerosols. The model is driven by historical and SSP370 (Meinshausen et al., 2020) forcing, and spans 1,850–2,100. Anomalies from the seasonal cycle and forced trend in the CESM2-LE are calculated by removing the ensemble mean.

3. The Relationship Between Skewness and the Magnitude of Extreme Heat

The PNW, like most locations on the westward edge of continents but unlike the majority of land areas in the Northern Hemisphere extratropics (McKinnon et al., 2016), experiences summertime temperature values that are, on average, positively skewed. For the June 15–July 15 period, skewness in temperature is most positive around the Puget Sound and Salish Sea, and decreases to the southeast, becoming negative around the border with Idaho (Figure 1a). Skewness is positive at most stations in Canada, even those far from the coast. In contrast, excess kurtosis is generally negative throughout the region, although noisier in its spatial structure than skewness, consistent with greater estimation challenges for higher-order moments (Figure 1b). While positive skewness values suggest a greater probability of hot extremes than a normal distribution, negative excess kurtosis values indicate reduced probability of both extremes.

The substantial predictive power of skewness for the magnitude of extreme events can be seen by examining the relationship across stations between skewness (calculated without the 2021 data) and the standardized magnitude of the 2021 heat wave. The magnitude is taken from the hottest day at each particular station in the June 27–July 1, 2021 period; the hottest temperatures were most commonly recorded on June 29 and 30. Stations with more positive skewness tended to have larger temperature anomalies, measured in units of standard deviations to account for differences in variability, during the heatwave (Figure 1d, $r = 0.76$). There is a similar but weaker relationship between excess kurtosis and heat wave magnitude (Figure 1e); however, skewness and excess kurtosis themselves are related in a parabolic space, so the relationships are not independent.

The result that climatological skewness is strongly related to the standardized magnitude of the 2021 heatwave across the domain motivates the question: can we better estimate the probability of the record-breaking PNW heatwave through accounting for the underlying statistical characteristics of the data? This line of questioning is motivated by limitations in two prior approaches to estimating the probability of this very extreme event. First, from a statistical perspective, Philip et al. (2021) fit a non-stationary GEV distribution to annual maxima PNW temperatures up to 2020, a standard approach for estimating the probability of extreme events. However, despite the GEV fitting the 1950–2020 data well, the 2021 event was predicted to have a probability of zero. Second, initial analyses of subseasonal forecasting (Bercos-Hickey et al., 2022; Lin et al., 2022) and climate (Pendergrass et al., 2021) model ensembles tend to find that dynamical models cannot produce temperature anomalies as large as observed in advance of peak summer. Given the record-breaking nature of the heatwave, as well as the high likelihood that it was an unusual event even given historic climate change, we turn to simulated data in order to produce a data set sufficiently large to capture very extreme events.

Previously, Sardeshmukh et al. (2015) proposed the use of a stochastically-generated skewed (SGS) distribution for this purpose, which can produce synthetic data with specified values of skewness, kurtosis, and autocorrelation, within certain limits. However, the SGS is constrained by a curve relating skewness and kurtosis, and temperatures in the PNW tend to have kurtosis values lower than this constraint. As an alternative approach, we use a climate model large ensemble, CESM2-LE, as our source of simulated data. We subset the model to the June 15–July 15 period to ensure similar seasonality, and constrain our simulated data to be over land between 40°N and 70°N, which spans the climatological latitude range where blocking atmospheric highs tend to occur (Barriopedro et al., 2006). Notably, we do not subset the climate model data to the PNW only. Rather, we ask the more general question: across regions with similar climatological skewness and kurtosis to each station in the PNW, what is the probability of seeing temperature anomalies at least as great as those observed in 2021?

The strong relationship between skewness and kurtosis, and the magnitude of very extreme events, is confirmed within CESM2. The most extreme event simulated across the CESM2-LE at each gridbox over land grades from being consistently less than 3σ with negative skewness and kurtosis (lower left of skewness/kurtosis space) to consistently greater than 5σ for high skewness and kurtosis (Figures 2a and 2b). While there are exceptions to this behavior, indicating that skewness and kurtosis are not the sole controls on the magnitude of extreme events, they summarize the bulk behavior across the data. In general, the relationship between skewness and kurtosis, and maximum temperatures, is consistent across CESM2 and the station data for the 2021 heatwave.

To make the comparison more quantitative, we resample the observed data with replacement, using a block size of 1 year, to obtain multiple estimates of skewness and kurtosis from each weather station, thereby accounting for the uncertainty in estimating higher-order moments from limited data, which can be substantial (Figure S3 in Supporting Information S1). The skewness/kurtosis pair for each resampled time series is matched with the gridbox in CESM2 with the closest (in terms of Euclidean distance) skewness and kurtosis values. The resampling is performed $N = 100$ times; however, the number of unique gridboxes identified as the closest match to each station is smaller (median of 73; minimum of 24; maximum of 95). We then compare various metrics of extreme events across the CESM2 gridboxes with the observed 2021 anomalies. As suggested by Figure 2a, it is necessary to look at the most extreme event (maximum across 50 ensemble members × 150 years = 8,550 years of data) in order to simulate similar behavior. For all but one station in the region (which had the greatest standardized temperature anomaly of 5.4σ), a nonzero

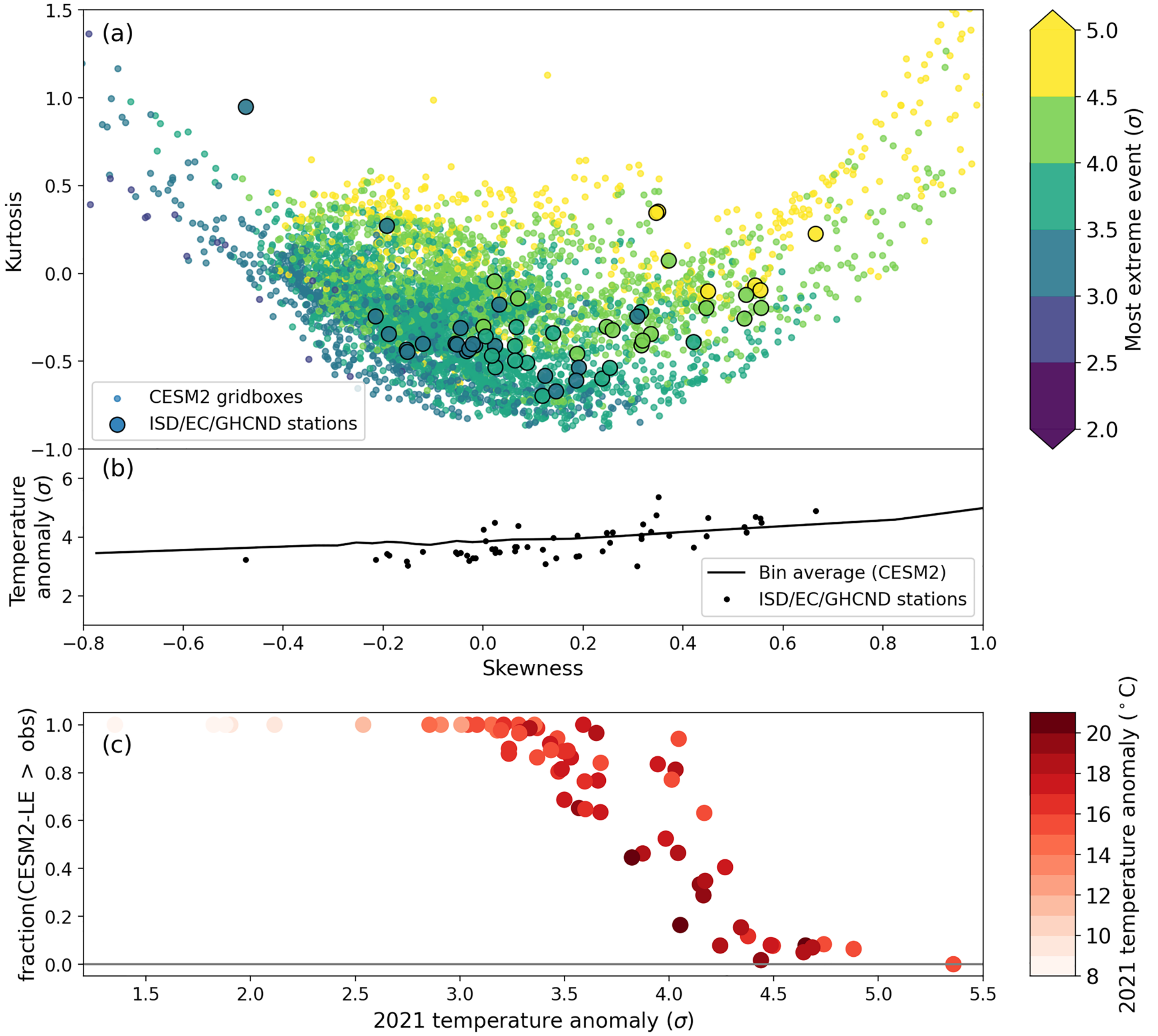

Figure 2. (a) The largest standardized maximum temperatures (Tx) anomaly across the Community Earth System Model version 2 Large Ensemble (CESM2-LE) simulations as a function of skewness and kurtosis at each gridbox between 40°N and 70°N. The 2021 record-breaking standardized Tx anomalies for the station data are shown in circles outlined in black. (b) The average of the maximum standardized temperature anomalies in CESM2 in each skewness bin (line) and the maximum standardized temperature anomaly in the station data as a function of skewness (dots). (c) The fraction of CESM2 gridboxes with skewness and kurtosis values consistent with each Pacific Northwest station that produce a maximum standardized Tx anomaly greater than the observed standardized 2021 anomaly.

fraction of gridboxes in CESM2 with similar climatological statistics have a maximum value that exceeds the standardized 2021 anomaly (Figure 2c). This result indicates that a modern climate model is able to simulate very extreme values comparable to those observed in 2021. However, it also suggests that their probability in CESM2 is astonishingly small: for the most extreme anomalies (exceeding 4.5σ), on average 6% of the maxima across gridboxes were more extreme than 2021. This suggests a probability on the order of 0.06 × 1/8,500 ≈ 0.00001 (one in a hundred thousand years), which could not be easily estimated with a smaller ensemble or more limited spatial sampling.

4. Estimating Probabilities of Record-Breaking Events With the Generalized Extreme Value Distribution

We now return to the question of estimating the probability of never-before-seen extreme events through fitting a GEV to the prior data. Specifically, we identify 351 gridboxes in CESM2 with similar statistics to PNW stations and where the hottest seasonal maxima across 1850–2020 and 50 ensemble members is at least a 4σ event (see red points in Figure S4 of Supporting Information S1; gridboxes that meet these criteria for more than one station are only included once). At each gridbox, we identify the ensemble member with the largest temperature anomaly, and fit a GEV to the seasonal maxima temperature anomalies for the 71 years of simulation before the extreme temperature occurs. The choice of 71 years is consistent with the analysis of Philip et al. (2021), who fit a GEV to ERA5 data from 1950 to 2020. In the case where the extreme temperature occurs before the 72nd year of the simulation, the GEV is fit with the first 72 years, excluding the year of the extreme temperature. For 350 out of 351 gridboxes, the GEV is found to be an appropriate model for the data based on a one-sample Kolmogorov-Smirnov test for the null hypothesis that the data were drawn from a GEV (p-values > 0.05). Recall that all temperature anomalies are relative to the CESM2 ensemble mean, which is assumed to capture the forced (non-stationary) climate change component of the data. As such, unlike Philip et al. (2021), we fit a stationary GEV to the 71 seasonal maxima values (see Figure S5 in Supporting Information S1 for an example).

The true probability of the extreme event in each case is on the order of 1/8,550 ≈ 0.0001 (one occurrence across 171 years and 50 ensemble members in CESM2-LE): a very small but nonzero probability. For 64% of the gridboxes, the GEV predicts a zero probability of the hot temperature anomaly, analogous to the result found for the 2021 PNW heatwave. This is due to the inference of a negative shape parameter in the GEV, which leads to a finite upper bound on the support of the distribution. While this result is not necessarily surprising given that it is unclear whether a season is a long enough block length (Huang et al., 2016; Veneziano et al., 2009) and/or 71 years is sufficient to evaluate the parameters of the distribution, it highlights an important limitation of GEV-based analyses for very extreme events in climate.

5. Is the Probability of Having a Very Extreme Event Changing?

The prior analysis suggests that, even after accounting for changes in mean temperature due to anthropogenic influence and the non-normality of daily temperature, the 2021 PNW heatwave was a very low probability event, although one that still can be simulated within a modern climate model. Is there evidence that the probability of these very extreme events is changing, beyond what would be expected from a shift in the mean?

We first return to the observations to assess whether, in advance of 2021, the upper tail of temperatures were warming more than the middle of the distribution. To do so, we estimate the sensitivity of the 50th, 95th, and 99th percentiles of daily temperatures during June 15-July 15 to the concurrent low-pass filtered global mean temperature using quantile regression (Haugen et al., 2018; Koenker and Bassett Jr, 1978; McKinnon et al., 2016), with a focus on the differences in trends between the upper percentiles and the 50th percentile. Significance of differences in trends is assessed by resampling the time series with a block size of one season; a p-value is estimated as the fraction of the bootstrapped differences that are of the opposite sign from the best estimate of the difference.

Across 43 out of 69 of the stations in the region, the trend in the 95th percentile of summer temperatures, β_{95}, is greater than that of the 50th percentile, β_{50} (Figures 3a–3c). However, excepting the northern part of the domain, there is not a clear spatial separation between stations that show greater versus less warming in the upper percentiles, suggesting that the differences may not be significant. Indeed, even large (>2°C/°C) differences in the 95th percentile compared to the 50th are not found to be significant when controlling for a false discovery rate of 0.1. That said, the spatial coherency of the amplified trends in the upper tail in the northern part of the domain may indicate a true signal that could be better identified by formally sharing information between stations and/or with longer records: all northern stations are from ISD, so trends are only estimated from 1977 to 2020. Similar results hold when comparing the 99th and 50th percentiles (Figure S6 in Supporting Information S1).

While the historical data before the 2021 season do not suggest greater warming in the upper tail of the distribution, they also do not represent the true forced response due to sampling of internal variability. We thus return to the CESM2-LE to assess whether there is evidence that the *variability* of the ensemble is changing to increase the probability of very hot extremes after accounting for changes in the mean state (by removing the ensemble mean). Across all gridboxes with daily temperature statistics similar to the PNW (black and red points in Figure S4 of Supporting Information S1), we calculate an approximate probability of exceeding various thresholds based on the 1850–2020 period (90th, 95th, 97.5th, 99th, 99.9th percentiles, and maximum value of seasonal maxima) for each year as the count of events greater than each threshold averaged across area-weighted gridboxes and ensemble members. For the 2000–2100 period, there is not a significant linear trend in the probabilities of events

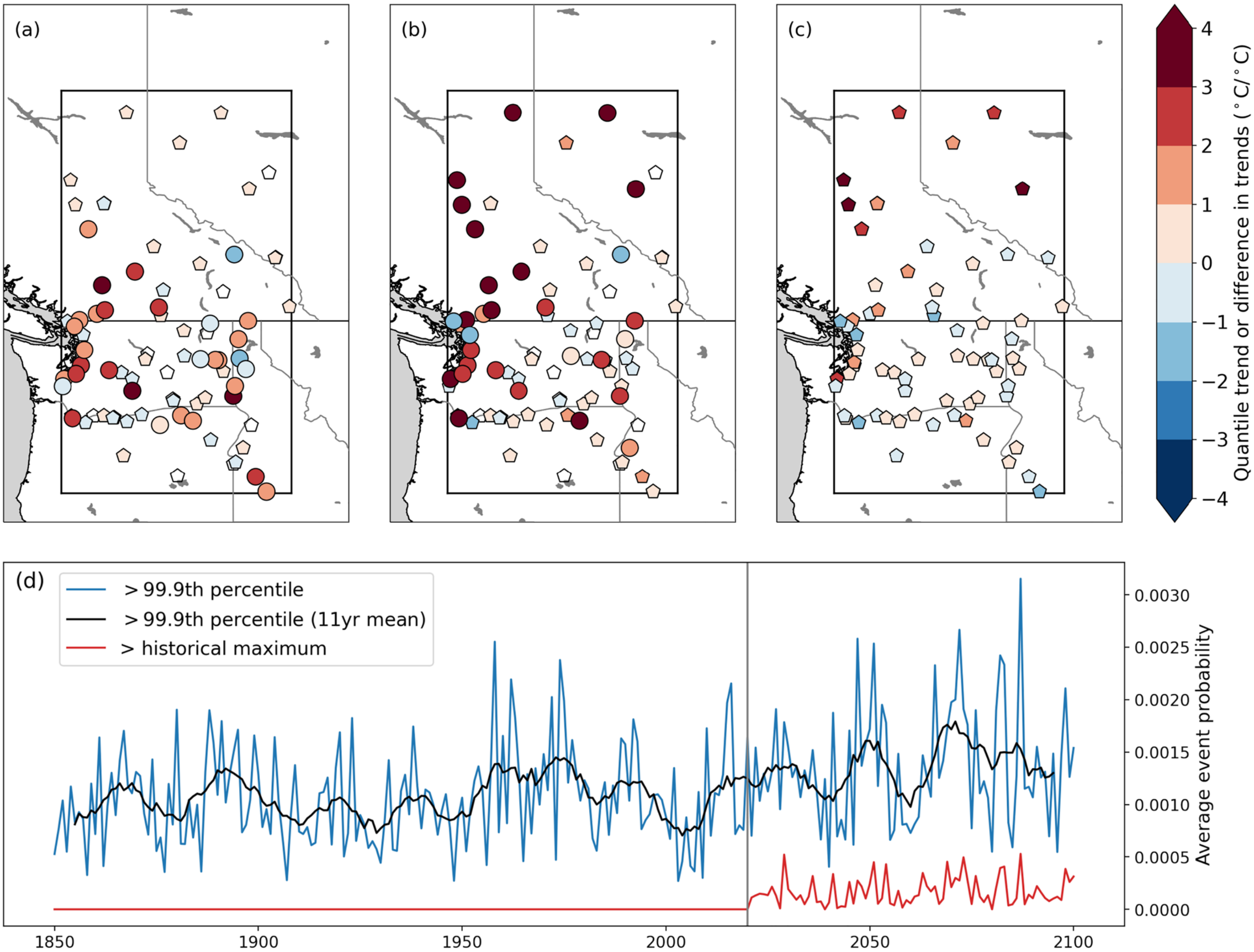

Figure 3. Trends, per degree global mean temperature change, in the (a) 50th, (b) 95th, and (c) 95th minus 50th percentiles of June 15-July 15 temperatures. In all panels, circles indicate trends (or differences in trends) that are significant after controlling for a false discovery rate of 0.1, whereas the smaller pentagons indicate lack of significance. The different stations have different record lengths based on their data source (see text and Figure S2 in Supporting Information S1). (d) The empirical probability of heat events exceeding the historical 99.9th percentile (blue; 11-year running mean in black) and the historical maximum (red) in Community Earth System Model version 2 Large Ensemble.

exceeding the 90%, 95%, and 97.5% percentiles when controlling for a false discovery rate of 0.1; in contrast, trends in the most extreme events (those exceeding the historical 99th and 99.9th percentiles, and historical maximum) are significant and positive (Figure 3d and Figure S7 in Supporting Information S1). Strikingly, the probability of an event exceeding the historical maximum is zero by definition before 2021, but is nonzero nearly every year subsequently. That said, the probabilities remain small: an average of 0.001 (one in a thousand years) between 2020 and 2050 for an event exceeding the historical 99.9th percentile, and an average of 0.0001 (one in ten thousand years) for an event exceeding the historical maximum.

6. Discussion and Conclusion

The record-breaking 2021 PNW heatwave raised many questions for the climate science community that we are only now beginning to answer. In this work, motivated by limitations in estimating the probability of the event using either statistical (Philip et al., 2021) or climate modeling (Bercos-Hickey et al., 2022; Lin et al., 2022; Pendergrass et al., 2021) methods, we focus on the role of non-normality in increasing the probability of the heat event beyond what would be expected in the case of a normal distribution. In particular, the magnitude of climatological skewness at weather stations across the PNW region is found to be a good predictor of the standardized magnitude of the maximum temperature during the 2021 heat wave. We then use a large ensemble to estimate the probability of an event as extreme as the 2021 PNW event given the climatological skewness and kurtosis of each weather station. For all but the most extreme anomaly, we find analogs with CESM2-LE wherein a simulated standardized temperature anomaly exceeded that observed in the PNW in 2021. While this indicates that climate models *can* simulate these very extreme events, the analysis also shows that the probabilities are shockingly low. In particular, it is necessary to look at the most extreme event across 171 years and 50 ensemble members to capture a similar extremity. Further, for very large events (e.g., exceeding 4.5σ at a weather station), only a small minority of CESM2-LE analogs in skewness/kurtosis space produce similarly extreme events.

Using the large ensemble, it is also possible to estimate whether the probability of very extreme events is projected to change in the future beyond what is expected from a change in the mean. Intriguingly, while CESM2-LE does not suggest any significant change in moderately extreme events (up to the 97.5th percentile), the likelihood of the most extreme events, including events that exceed anything observed in the historical period, is found to increase for gridboxes with similar temperature statistics as the PNW. Future work should dissect the physical mechanisms that lead to these very extreme events in order to further validate and understand their occurrence in CESM2-LE.

While our analysis is able to demonstrate that events as extreme as the PNW heatwave occur in climate models, as well as illustrate why a GEV fitted to historical data could estimate a zero probability of an event that can occur, we do still find that the probability of the 2021 event was miniscule. Does the fact that it occurred in our single observational record cast doubt on these probability estimates from climate models? The ability to answer this question is confounded by selection bias: we are studying the PNW heatwave *because* it was so extreme. Assuming an average persistence of a weather system of 7 days, and 30 spatial degrees of freedom across the globe, we have records of ≈156,000 distinct weather events over the past 100 years, some of which are liable to be very extreme by chance. Assuming a similar event does not occur in the near future, and without a clear physical link to climate change, the most likely explanation remains that the weather event itself was "bad luck." While climate change added additional warming to the picture (approximately 1.5°C since 1960), the event would have been severe even without the climate change signal. However, if similar events do start to occur with greater frequency than expected based on the probabilities presented here, it will be necessary to revisit the analysis and consider whether our climate models are accurately capturing their probability. A complete analysis of the Northern Hemisphere summer temperatures during 2022 may prove illuminating.

In line with prior work, our analysis has focused on daily maximum temperature alone. The impacts of heat extremes also depend on other metrics, including daily minimum temperature (Tn). In general, Tx and Tn heatwaves can be caused by distinct processes, and the two do not necessarily co-occur (Bumbaco et al., 2013). In this case, the heat wave arguably was both a Tx and Tn heatwave: while the largest Tn anomalies during the heatwave were smaller than those of Tx, they were comparable when measured in standard deviation units. However, in contrast to our findings for Tx, the climatological Tn skewness of a weather station is a poor predictor of the magnitude of its 2021 standardized Tn anomaly, suggesting that other factors besides random sampling of a long upper tail in Tn were relevant for the event. Looking forward, it is advisable to consider the PNW heatwave as a compound event, and aim to understand the causes that led to not only high Tx, but also high Tn.

Data Availability Statement

All station data is publicly available at https://www.ncei.noaa.gov/data/global-hourly/a (ISD), https://www1.ncdc.noaa.gov/pub/data/ghcn/daily/ (GHCND), and https://climate.weather.gc.ca/historical_data/search_historic_data_e.html (EC). Access to the CESM2-LE is through the National Center for Atmospheric Research Climate Data Gateway and is documented at https://www.cesm.ucar.edu/projects/community-projects/LENS2/data-sets.html. Code to reproduce the figures and other results is available at https://github.com/karenamckinnon/record_breaking_heat.

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