How unexpected was the 2021 Pacific Northwest heatwave?

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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.
- 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.

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 (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.

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 impacts of the heat wave, especially on human life, were likely exacerbated by the fact that the region is known for a more 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 westward along a midlatitude wave guide, and modifying 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 (*Philip et al.*, 2021; *Neal et al.*, 2022). The propagating circulation anomaly was also associated with a cross-Pacific atmospheric river, which 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 is 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 (*Philip et al.*, 2021; *Overland*, 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 and 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 occurrence of the heatwave suggests that the probability of very extreme events is changing faster than a change in the mean would suggest. This hypothesis is not supported by a prior analysis of trends in the 50th and 95th percentiles of station data during peak summer from 1980-2015 (*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 distribution fit to the data through 2020 (i.e. not including the 2021 event) predicted that the probability of observing 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-40°C, depending on the location), with no significant trend 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. 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, to characterize the background distribution of temperature, and a large ensemble of climate model simulations to gain a more complete sample of the probability of very extreme events, as well as their changes. 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 its 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 focus on 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), as well as the strong seasonality in daily temperature statistics and circulation patterns, we limit all of our analyses to the 30-day period of June 15-July 15. We focus on the domain of 43-57°N, 115-123°W, which spans the maximum anomalies of the heatwave.

We use three different sets of data in order to maximize the 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 dataset is indicated in Figure S2. 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 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 yr^{-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 dataset 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 1850-2100. Anomalies from the seasonal cycle and forced trend in the CESM2-LE are estimated 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 (*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). Notably, skewness remains 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, shown here as the hottest day at that particular station in the June 27-July 1 period. (The hottest temperatures were most commonly recorded on June 29 and 30.) Stations with a more positive skewness tended to have hotter temperatures during the heatwave (Figure 1d, r = 0.76), as measured in standard deviation units in order to normalize for differences in variability. There is a similar but weaker relationship between excess kurtosis and heat wave magnitude (Figure 1e); however, skewness and excess kurtosis themselves tend to be 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 to annual maxima in 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 (*Lin et al.*, 2022; *Bercos-Hickey 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 is an unusual event even given historic climate change, we turn to simulated data in order to produce a dataset 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 40-70°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 maximum 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 (Figure 2a,b). 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 for the 2021 heatwave, 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 one 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). 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 $\times$ 150 years = 8550 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 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 the 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 $0.06 \times 1/8500 \approx 0.00001$ (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, as was done in *Philip et al.* (2021). Given that these very extreme events do occur, if rarely, in CESM2, can we use the model simulations to illuminate the GEV behavior in estimating the probability of these events? To do so, we pull out 351 gridboxes in CESM2 with similar statistics to PNW stations and where the hottest seasonal maxima across 1850-2020 and across 50 ensemble members is at least a 4σ event (see red points in Figure S4; gridpoints that meet these criteria for more than one station are only included once). At each location, we identify the ensemble member with the largest temperature anomaly, and fit a GEV to the 71 years of simulation before the simulated heat wave occurs. The choice of 71 years is consistent with the analysis of *Philip et al.* (2021), who fit a GEV to ERA5 data from 1950-2020. In the case where the heat wave occurs before the 72nd year of the simulation, the GEV is fit with the first 72 years, excluding the heat wave year. Unlike *Philip et al.* (2021), we do not fit a non-stationary GEV, because the forced signal is removed by subtracting the ensemble mean before the analysis.

The true probability of the extreme events in each case is on the order of $1/8550 \approx 0.0001$ (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 the result is not necessarily surprising given that it is unclear whether a season is a sufficiently long block length (*Veneziano et al.*, 2009; *Huang et al.*, 2016) and whether 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 in the region, 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 (*Koenker and Bassett Jr*, 1978; *McKinnon et al.*, 2016; *Haugen et al.*, 2018), 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} (Figure 3a-c). 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 could indicate a true signal of greater warming in the upper tail that could be identified by formally sharing information between stations and/or with longer records; all stations in that region are from ISD, which only span 1977-present in Canada. Similar results hold when comparing the 99th and 50th percentiles (Figure S5).

While the historical data from before the 2021 season does not suggest a significant change in variability that would lead to a greater warming in the upper tail of the distribution, it also does not represent the true forced response due to sampling related to internal variability. We thus return to the CESM2-LE to assess whether there is evidence that the *variability* of the ensemble is changing in a manner that would lead to a higher 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 points in Figure S4), 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 beyond each threshold averaged across area-weighted gridboxes and ensemble members (Figure 3d). For the 2000-2100 period, there is not a significant linear trend in the probabilities of events 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 S6). 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 2020-2050 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 (*Lin et al.*, 2022; *Bercos-Hickey 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 magnitude (in standard deviation units) 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, at a station that recorded a 5.4σ event, 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 simulate 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 alone. 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 simulation, 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: as a community, 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 $\approx$ 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), it is clear that the event would have been severe even without the climate change signal.

In line with prior work, our analysis has focused on daily maximum temperature alone. The impacts of heat extremes also depend on other metrics, such as daily minimum temperature, heat wave duration, and the co-occurring humidity levels (e.g. *Anderson and Bell*, 2009, for mortality). In general, Tn heatwaves are more likely to be associated with high precipitable water and longwave heating as opposed to large-scale geopotential height anomalies for Tx heatwaves, 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 daily minimum (Tn) temperature anomalies during the heatwave were smaller than those of daily maximum temperature (e.g. an average Tn anomaly of 11.3°C across stations for which 2021 was a record breaking heatwave for Tn, compared to an average Tx anomaly of 17.0°C), the average standardized anomaly in Tn was actually greater than Tx (4.2σ compared to 3.8σ). However, in contrast to our findings for Tx, the climatological skewness of a weather station is a poor predictor of the magnitude of its 2021 standardized temperature 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.

7 Open Research

All station data is publicly available at `https://www.ncei.noaa.gov/data/global-hourly/access` (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 process and analyze all data, and make all figures, will be made available on K.A.M.'s public github page (`https://github.com/karenamckinnon`) upon publication.

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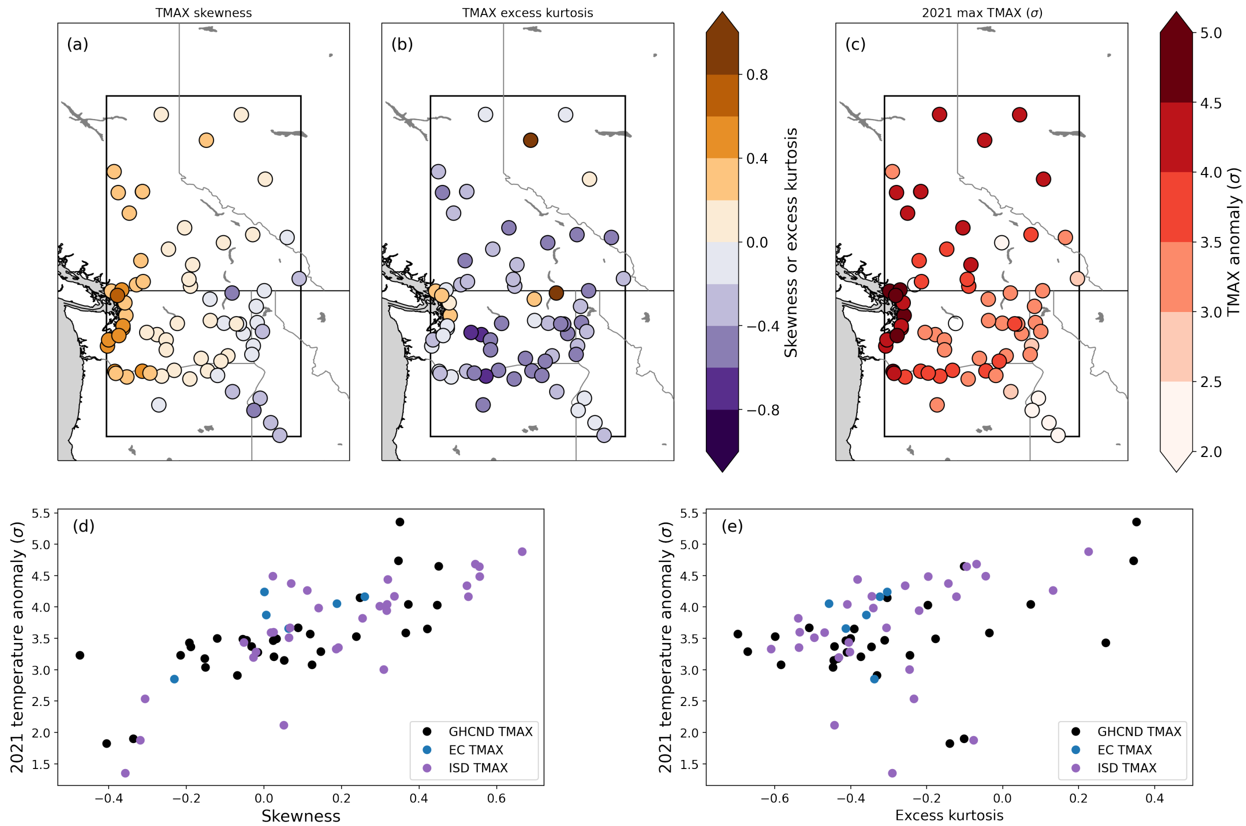

Figure 1: (a) The skewness of Tx at each station. (b) The excess kurtosis of Tx at each station. (c) The maximum temperature anomaly during the 2021 heatwave, measured in standard deviations (σ). (d) The relationship between skewness and maximum 2021 temperature anomaly across stations. (e) The relationship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

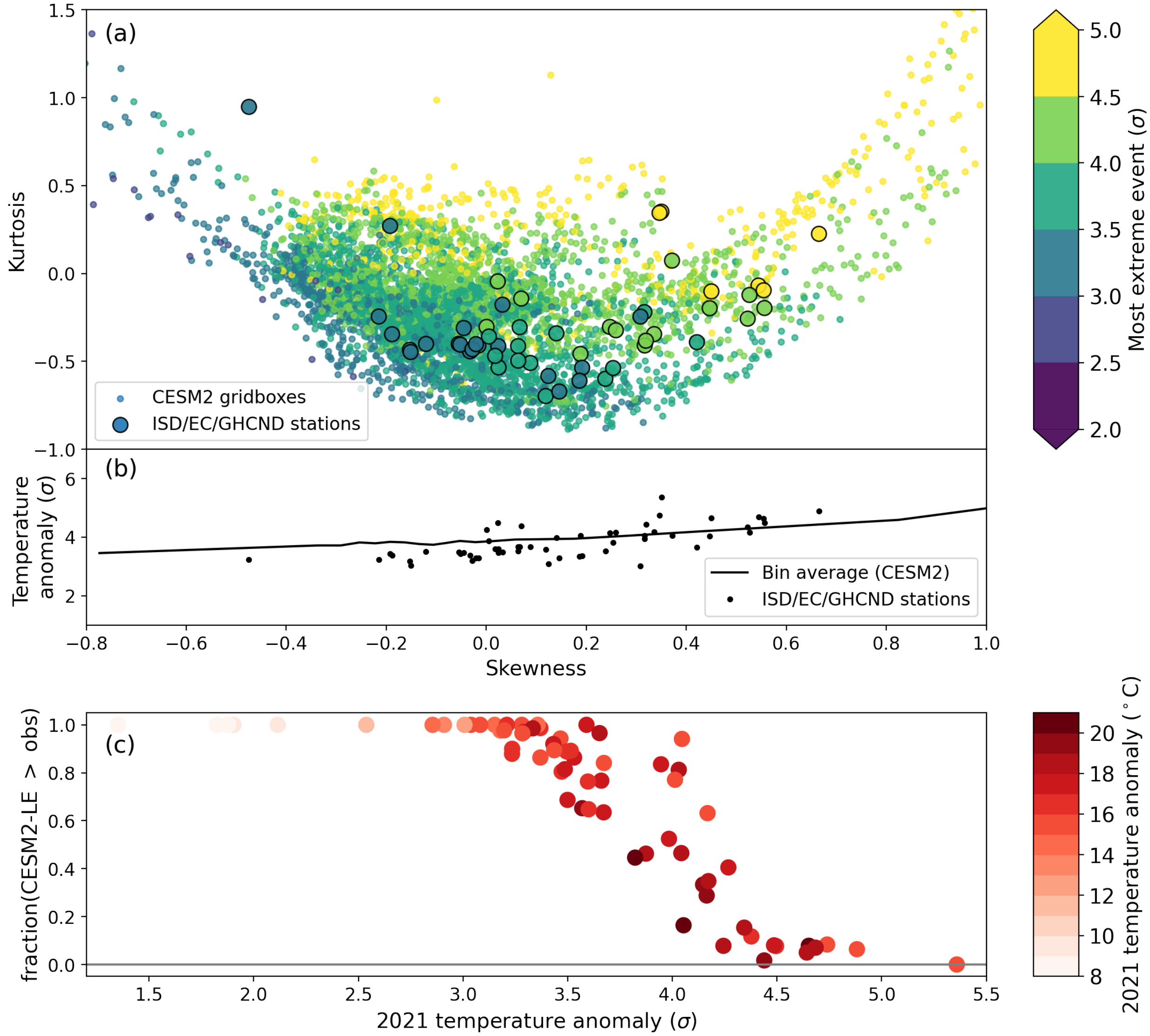

Figure 2: (a) The largest Tx anomaly across the CESM2-LE simulations (50 ensemble members times 171 years = 8550 total years) in standard deviation units as a function of skewness and kurtosis at each gridbox between 40-70°N. The 2021 record-breaking Tx anomalies for the station data is shown in circles outlined in black. (b) The average of the maximum standardized temperature anomalies in CESM2 in each skewness bin (black line) and the maximum temperature anomaly in the station data as a function of skewness. (c) The fraction of CESM2 gridboxes with skewness and kurtosis consistent with each PNW station which have a maximum Tx anomaly greater than the observed 2021 anomaly.

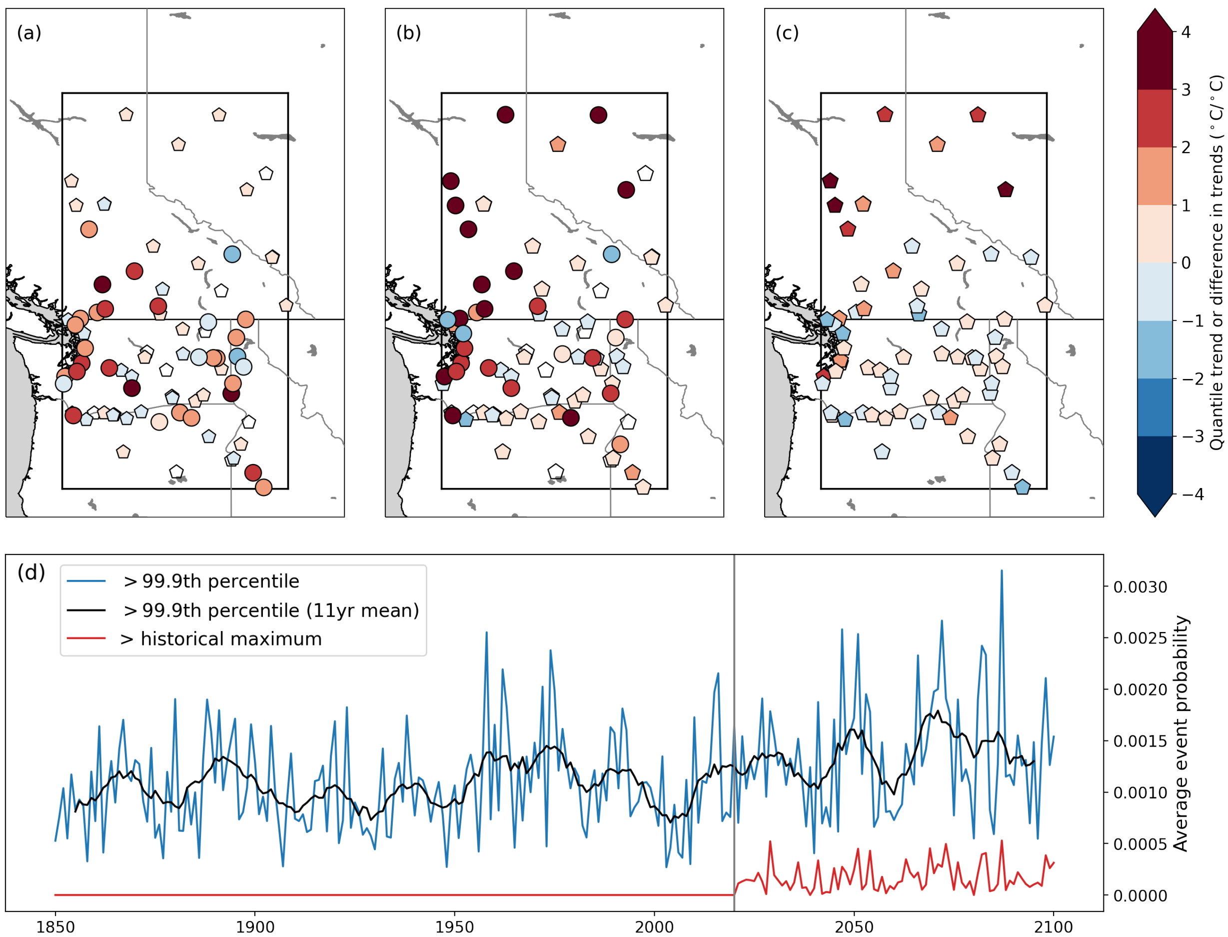

Figure 3: Trends, per degree global mean temperature change, in the (a) 50th, (b) 95th, and (c) 95th minus 50th percentiles of June 15-July 15 temperatures. In all panels, circles indicate trends (or differences in trends) that are significant after controlling for a false discovery rate of 0.1, whereas the smaller pentagons indicate lack of significance at that level. Note that the different stations have different record lengths based on their data source (see text and Figure S2). (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).

9 Supplementary Figures

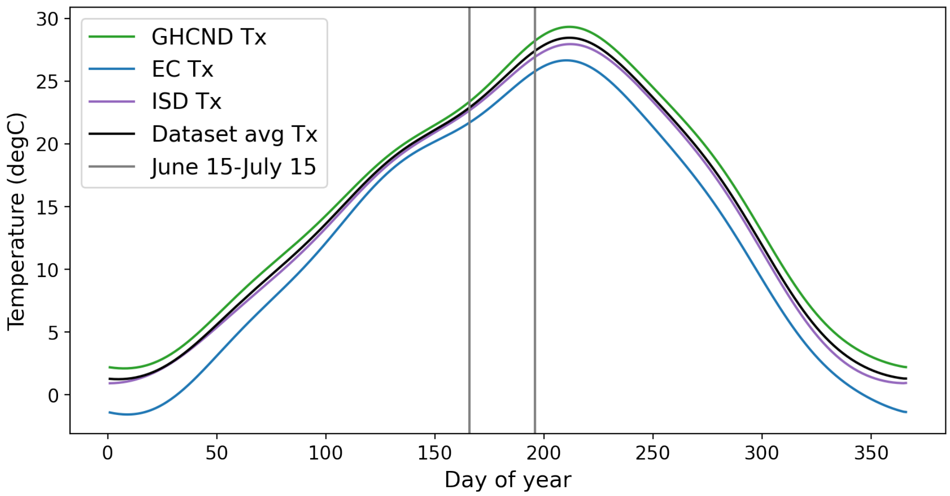

Figure S1: The seasonal cycle of Tx in the Pacific Northwest. The seasonal cycle in each dataset is estimated as the average across stations, and then projected onto the first five annual-period harmonics. The different average value in each dataset is a function of the unequal spatial distribution of stations. The June 15-July 15 period of study is bracketed by vertical gray lines, and occurs in advance of peak summer.

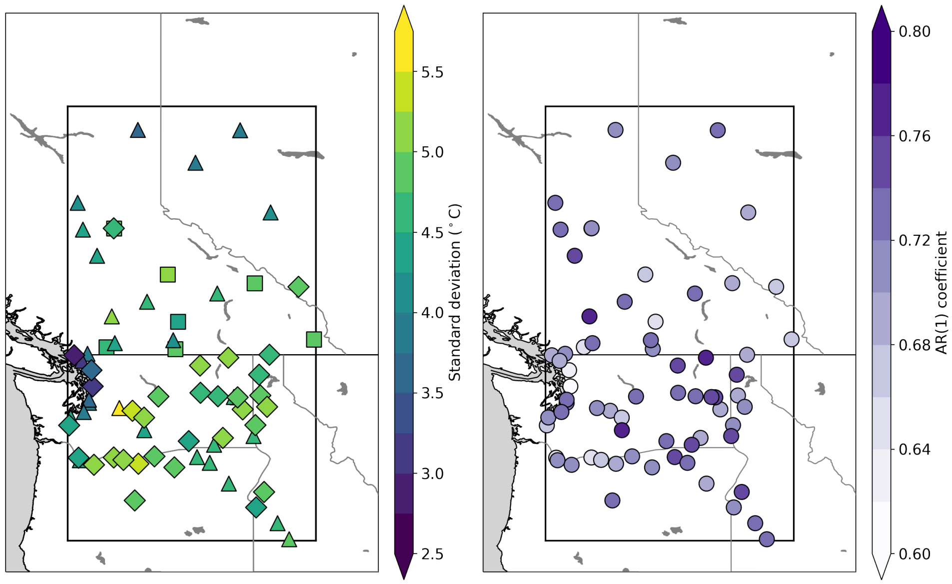

Figure S2: The sample standard deviation (left) and lag-1 day autocorrelation coefficient (right) for each station. The lefthand map also shows the data source for each station: Environment Canada = square; Integrated Surface Database = triangle; Global Historical Climatology Network Daily = diamond

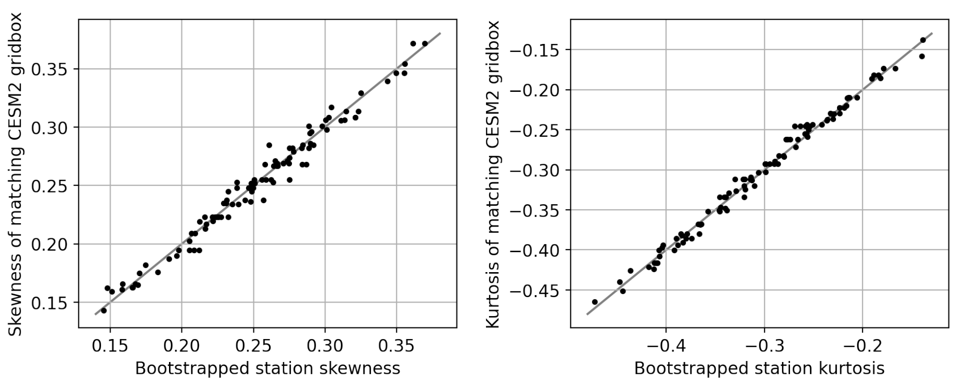

Figure S3: An example showing the identification of CESM2 gridboxes with similar skewness and kurtosis values to a given weather station. The horizontal axis in both panels shows values of skewness and kurtosis for daily maximum temperature during the June 15-July 15 period estimated for a single weather station (GHCND station CA001090660 in Barkerville, British Columbia, Canada; data from 1900-2021) based on resampling years of the record with replacement. The vertical axis shows the values of skewness and kurtosis for CESM2 gridboxes chosen to most closely match (as measured by Euclidean distance) the bootstrapped values from the station data. The one-to-one line is shown in gray. Across all stations and bootstrap samples, the correlation between the station value and the CESM2 value is 0.987 for skewness, and 0.998 for kurtosis.

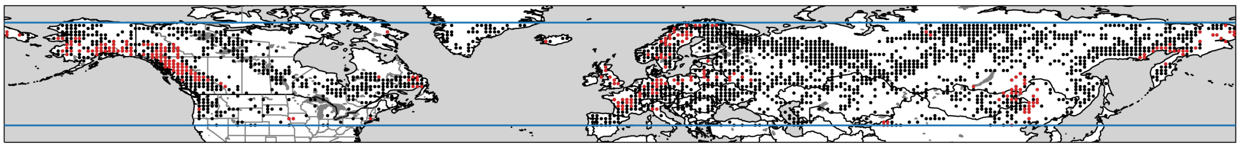

Figure S4: The location of gridboxes in CESM2 that have similar skewness and kurtosis to at least one station in the Pacific Northwest domain. Red dots indicate a CESM2 gridbox where (1) the “matching” PNW weather station had a temperature anomaly during the 2021 heatwave that exceeded 4σ, and (2) the CESM2 gridbox had a maximum temperature that exceeded the value from the weather station (in σ units).

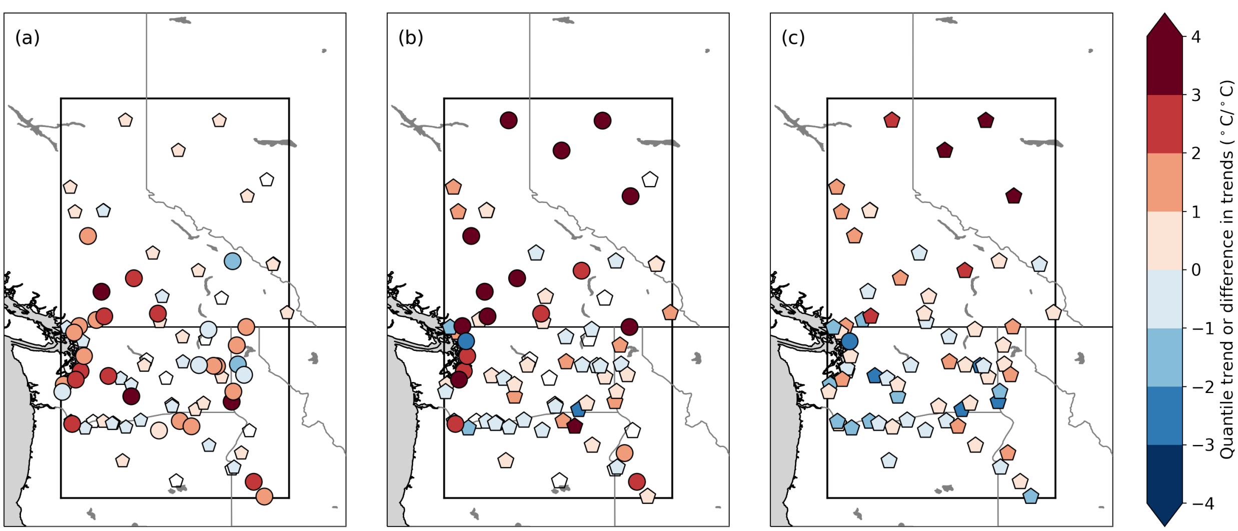

Figure S5: As in Figure 3a-c, but (b) shows the 99th percentile, and (c) shows the difference between the 99th and 50th percentiles.

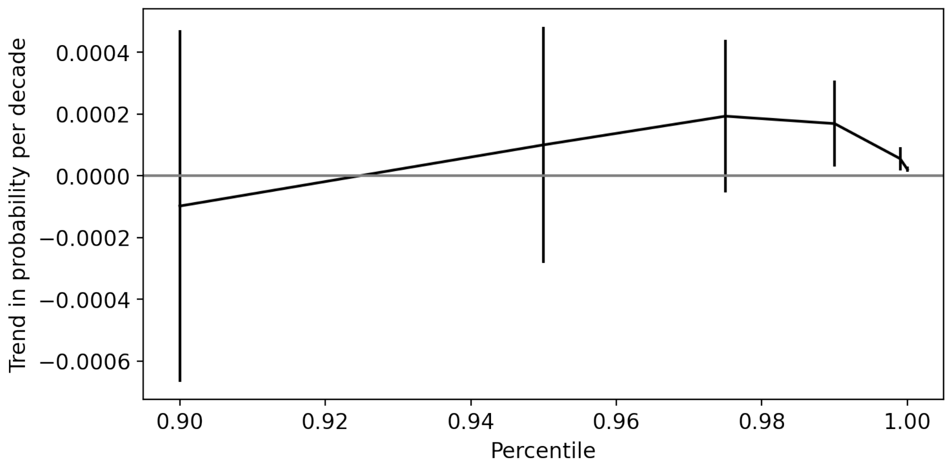

Figure S6: The linear trend from 2000-2100 in the estimated probability of extreme events in CESM2, where ‘extreme’ is defined by exceeding the various percentiles on the horizontal axis. The vertical bars at each point show the 95% confidence interval, and the zero line is shown in gray. The trends are found to be significant after controlling for a false discovery rate of 0.05 when extremes are defined as those at least exceeding the 99th percentile.