
Heat Waves

Identification

1. Indicator Description

This indicator examines several characteristics of extreme heat events, also known as heat waves, across the United States over the last several decades. As average temperatures rise, scientists expect heat waves to become more frequent and intense (USGCRP, 2017). Unless people and communities can adapt to these changing conditions, increased heat waves could also lead to an increase in deaths and illnesses from heat, particularly among vulnerable populations, such as children, the elderly, economically disadvantaged groups, and those with chronic health conditions made worse by heat exposure (Sarofim et al., 2016). Therefore, it is useful to track trends in heat waves as a noticeable effect of climate change as well as a risk factor for human health.

Components of this indicator include:

- Decadal averages of four heat wave characteristics—frequency, duration, season length, and intensity—averaged across 50 large metropolitan areas from 1961 to 2019 (Figure 1).
- Absolute change of each of these four heat wave characteristics for individual metropolitan areas from 1961 to 2019 (Figure 2).
- An index reflecting the frequency and spatial extent of extreme heat events across the contiguous 48 states from 1895 to 2020 (Figure 3).

2. Revision History

April 2021: Published indicator, including new components (Figures 1 and 2) and heat wave index that had previously been published as part of the High and Low Temperatures indicator (Figure 3).

Data Sources

3. Data Sources

Figures 1 and 2. Heat Wave Characteristics, 1961–2019

Data for this indicator were obtained from the National Oceanic and Atmospheric Administration’s (NOAA’s) National Centers for Environmental Information (NCEI). NCEI maintains an “apparent temperature” data set for 187 metropolitan statistical areas (MSAs) in the United States. This data set combines temperature and humidity to calculate apparent temperature, which relates more closely to heat stress on the human body than temperature alone. Data for both figures were downloaded from NCEI and processed by EPA. An earlier version of this analysis for the 1961–2010 period was published by Habeeb et al. (2015); it forms the basis for Figures 1 and 2.

Figure 3. U.S. Annual Heat Wave Index, 1895–2020

Index values for Figure 3 were provided by Dr. Kenneth Kunkel of NOAA’s Cooperative Institute for Climate and Satellites (CICS), who updated an analysis that was previously published in U.S. Climate Change Science Program (2008).

4. Data Availability

Figures 1 and 2. Heat Wave Characteristics, 1961–2019

NCEI’s apparent temperature data are publicly available at: www.ncdc.noaa.gov/societal-impacts/heat-stress/data. This source includes percentile threshold values that NCEI has calculated for each MSA. Underlying temperature and humidity measurements come from weather stations overseen by NOAA’s National Weather Service (NWS). NCEI maintains a set of databases that provide public access to daily and monthly temperature records from these weather stations. For access to these data, see NCEI’s website at: www.ncdc.noaa.gov. There are no confidentiality issues that may limit accessibility. For an inventory of stations and station metadata, see: www.ncdc.noaa.gov/data-access/land-based-station-data.

Figure 3. U.S. Annual Heat Wave Index, 1895–2020

Data for this figure were provided by Dr. Kenneth Kunkel of NOAA CICS, who performed the analysis based on data from NCEI’s publicly available databases. Access to these databases is described in the previous paragraph regarding Figures 1 and 2.

Methodology

5. Data Collection

Since systematic collection of weather data in the United States began in the 1800s, observations have been recorded from 23,000 stations. At any given time, approximately 8,000 stations are recording observations on an hourly basis, along with the maximum and minimum temperatures for each day. Some of these stations are automated stations operated by NWS. The remainder are Cooperative Observer Program (COOP) stations operated by other organizations using trained observers and equipment and procedures prescribed by NOAA. For an inventory of U.S. weather stations and information about data collection methods, see: www.ncdc.noaa.gov/data-access/land-based-station-data, the technical reports and peer-reviewed papers cited therein, and the NWS technical manuals at: www.weather.gov/coop. Sampling procedures are also described in Kunkel et al. (2005) and in the full metadata for the COOP data set, available at: www.weather.gov/coop.

Figures 1 and 2 are based on hourly temperature and humidity measurements. NCEI selected one long-term weather station from each of the 187 MSAs for which to compute apparent temperature values. Specifically, NCEI selected airport stations because they tend to have long-term, highly quality-controlled records. These stations are listed in an inventory at: www.ncdc.noaa.gov/societal-impacts/heat-stress/data. MSAs are geographic regions with relatively high population density; each can include one or more major cities within its boundaries. Timeframes of data availability vary by MSA, depending on the continuity of weather stations, but NCEI was able to calculate apparent temperature

for most MSAs from the middle of the 20th century to present. This indicator begins at 1961 because nearly all large MSAs have apparent temperature data back at least that far.

Figure 3 is based on temperature data from stations within the contiguous 48 states from the COOP data set that had sufficient data during the period of record (1895–2020).

6. Indicator Derivation

Figures 1 and 2. Heat Wave Characteristics, 1961–2019

For each MSA, NCEI calculated daily maximum and minimum apparent temperature for each day based on hourly temperature and humidity measurements. NCEI derived apparent temperature using the following equation:

$$A = -1.3 + 0.92T + 2.2e$$

where A is the apparent temperature (°C), T is ambient air temperature (°C), and e is water vapor pressure (kilopascals). This equation was established by Steadman (1984). This approach is considered to be more directly relevant to human health than air temperature alone, because humidity affects the body's ability to cool off through perspiration. Hence, health warnings about extreme heat are often based on NWS's Heat Index, which is similar to apparent temperature in that it combines temperature and humidity (albeit with a different formula).

To narrow the data set and focus on extreme heat where the most people are potentially exposed, this indicator examines trends for the 50 most populous MSAs that had sufficient data from 1961 to 2019. "Sufficient data" means that a city was included in NOAA's apparent temperature data set and had at least 696 months of valid data out of the total of 708 months, which is consistent with the proportion required by Habeeb et al. (2015) (590 of 600 months). A month was considered valid if it had daily temperature data available for at least 60 percent of the days in the month (i.e., 17 days of data in February, both in leap years and non-leap years; 18 days of data for 30-day months; and 19 days of data for 31-day months). MSA populations are based on the 2010 decennial U.S. Census, available at: <https://www.census.gov/data/tables/time-series/dec/c2010sr-01.html>. Table TD-1 lists the top MSAs by population, identifies the 50 MSAs selected for this indicator, and identifies the reasons why other MSAs on the list could not be included.

Table TD-1. Metropolitan Areas Analyzed in This Indicator
Rank based on 2010 Census for each MSA as defined by the U.S. Census Bureau

Rank	MSA	Included	Excluded because it did not meet data availability criteria	Excluded because it did not have a station in NOAA's apparent temperature data set
1	New York–Newark–Jersey City, NY-NJ-PA		X	
2	Los Angeles–Long Beach–Anaheim, CA	X		
3	Chicago–Naperville–Elgin, IL-IN-WI	X		
4	Dallas–Fort Worth–Arlington, TX	X		
5	Philadelphia–Camden–Wilmington, PA-NJ-DE-MD	X		
6	Houston–The Woodlands–Sugar Land, TX		X	
7	Washington–Arlington–Alexandria, DC-VA-MD-WV (data for Sterling, VA)		X	
8	Miami–Fort Lauderdale–West Palm Beach, FL	X		
9	Atlanta–Sandy Springs–Roswell, GA	X		
10	Boston–Cambridge–Newton, MA-NH	X		
11	San Francisco–Oakland–Hayward, CA	X		
12	Detroit–Warren–Dearborn, MI	X		
13	Riverside–San Bernardino–Ontario, CA			X
14	Phoenix–Mesa–Scottsdale, AZ	X		
15	Seattle–Tacoma–Bellevue, WA	X		
16	Minneapolis–St. Paul–Bloomington, MN-WI		X	
17	San Diego–Carlsbad, CA	X		
18	St. Louis, MO-IL	X		
19	Tampa–St. Petersburg–Clearwater, FL	X		
20	Baltimore–Columbia–Towson, MD	X		
21	Denver–Aurora–Lakewood, CO			X
22	Pittsburgh, PA	X		
23	San Juan–Carolina–Caguas, PR	X		
24	Portland–Vancouver–Hillsboro, OR-WA	X		
25	Charlotte–Concord–Gastonia, NC-SC	X		
26	Sacramento–Roseville–Arden–Arcade, CA		X	

Rank	MSA	Included	Excluded because it did not meet data availability criteria	Excluded because it did not have a station in NOAA's apparent temperature data set
27	San Antonio–New Braunfels, TX	X		
28	Orlando-Kissimmee-Sanford, FL			X
29	Cincinnati, OH-KY-IN (data for Covington, KY)	X		
30	Cleveland-Elyria, OH	X		
31	Kansas City, MO-KS		X	
32	Las Vegas–Henderson–Paradise, NV	X		
33	Columbus, OH	X		
34	Indianapolis-Carmel-Anderson, IN	X		
35	San Jose–Sunnyvale–Santa Clara, CA			X
36	Austin–Round Rock, TX	X		
37	Virginia Beach–Norfolk–Newport News, VA-NC	X		
38	Nashville-Davidson-Murfreesboro-Franklin, TN	X		
39	Providence-Warwick, RI-MA	X		
40	Milwaukee–Waukesha–West Allis, WI	X		
41	Jacksonville, FL	X		
42	Memphis, TN-MS-AR	X		
43	Oklahoma City, OK	X		
44	Louisville/Jefferson County, KY-IN	X		
45	Hartford–West Hartford–East Hartford, CT	X		
46	Richmond, VA	X		
47	New Orleans–Metairie, LA	X		
48	Buffalo–Cheektowaga–Niagara Falls, NY	X		
49	Raleigh, NC	X		
50	Birmingham-Hoover, AL	X		
51	Salt Lake City, UT	X		
52	Rochester, NY	X		
53	Grand Rapids–Wyoming, MI		X	
54	Tucson, AZ	X		

Rank	MSA	Included	Excluded because it did not meet data availability criteria	Excluded because it did not have a station in NOAA's apparent temperature data set
55	Urban Honolulu, HI		X	
56	Tulsa, OK	X		
57	Fresno, CA	X		
58	Worcester, MA-CT			X
59	Bridgeport-Stamford-Norwalk, CT			X
60	Albuquerque, NM	X		
61	Albany-Schenectady-Troy, NY	X		
62	Omaha-Council Bluffs, NE-IA		X	
63	New Haven–Milford, CT			X
64	Bakersfield, CA			X
65	Knoxville, TN	X		
66	Greenville-Anderson-Mauldin, SC		X	
67	Oxnard–Thousand Oaks–Ventura, CA			X
68	Allentown-Bethlehem-Easton, PA-NJ	X		
69	El Paso, TX	X		

Figures 1 and 2 are based on the methodology used by Habeeb et al. (2015) to define and analyze heat waves, with some updates to reflect the evolution of the data and a need for additional statistical analysis. For consistency across the country, this indicator defines a heat wave as a period of two or more consecutive days where the daily minimum apparent temperature in a particular city is higher than the 85th percentile of historical July and August temperatures for that city. Historical July and August baseline temperatures are analyzed for a base period of 1981–2010, which was chosen for consistency with other climatology metrics. This indicator uses daily minimum temperature because studies show that the most direct relationship between mortality and elevated temperatures occurs in relation to the daily minimum (Habeeb et al., 2015; Sarofim et al., 2016), as warm nighttime temperatures prevent the body from cooling off after a hot day. Using the 85th percentile of July and August temperatures results in a threshold that equates to the nine hottest days in a typical summer—likely among the nine hottest days of the year. A temperature that is typically only recorded nine times during the hottest part of the year is rare enough that most people would consider it to be unusually hot. Using city-specific thresholds rather than a single nationwide threshold (e.g., 95°F) ensures that this indicator accounts for local variations in conditions, and it acknowledges differences in the extent to which people have acclimated or adapted to high temperatures. For example, a 95°F day in Milwaukee

could arguably pose a more severe health risk than a 100°F day in Phoenix, given the greater prevalence of air conditioning in Phoenix and the extent to which Phoenix residents are accustomed to hot weather.

NCEI calculates the 85th-percentile threshold for each MSA, both for minimum daily temperatures and for maximum daily temperatures. These values are publicly available on the NCEI website at: www.ncdc.noaa.gov/societal-impacts/heat-stress/data. Using these data, EPA compared each city's daily minimum apparent temperature records with that city's corresponding 85th-percentile threshold. EPA identified a heat wave whenever two or more consecutive days exceeded the threshold, then quantified the following four metrics for each city and each year:

- Frequency: the number of distinct heat waves that occur every year.
- Duration: the length of each individual heat wave, in days. These data can be aggregated to find the average duration of individual heat waves over a time period such as a year or a decade.
- Season length: the number of days from the first day of the first heat wave of the year to the last day of the last heat wave, including the first and last days in the count.
- Intensity: how hot the temperature is during a heat wave, compared with the corresponding city-specific threshold. For example, if a city has an 85th-percentile threshold of 95°F, and the average of the daily minimum apparent temperatures during a three-day heat wave was 98°F, the intensity would be recorded as 3°F above the threshold.

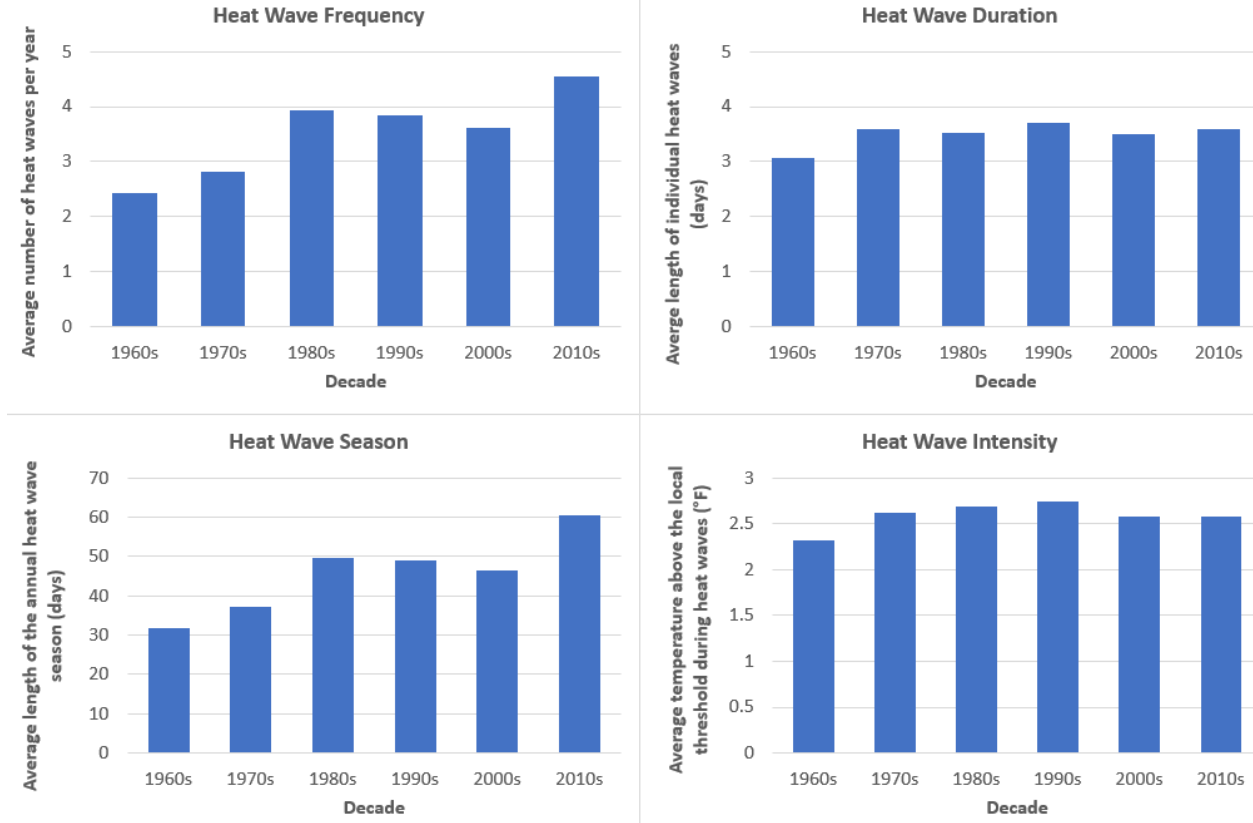
In a particular year, some cities may not have experienced any heat waves as defined by the thresholds described above. The appropriate treatment of these zero-heat-wave years depends on the metric. For frequency and season length, a city without heat waves in a given year is treated as having a frequency of zero heat waves and a season length of zero days for that year. Duration and intensity, however, are metrics that reflect the characteristics of heat waves that actually occurred: years without heat waves are excluded from any calculations (e.g., averages or regressions) based on these metrics, so as not to distort the results.

In Figure 1, these four characteristics are averaged by decade for each city, then aggregated nationwide using an unweighted average of the 50 MSAs in this analysis. This approach is particularly important for duration and intensity because it gives equal weight to every city. (Averaging the duration and intensity of all individual heat wave events would bias the results toward cities that happened to experience more heat waves.) Similarly, when the average duration and intensity are calculated by decade for each city, all heat wave events occurring in that decade are weighted equally, rather than averaging by year before averaging for the decade. "1960s" represents the average from 1961 to 1970, "1970s" is 1971–1980, and so on. "2010s" is a partial decade, reflecting data from 2011 to 2019.

The maps in Figure 2 show long-term trends in the four heat wave characteristics for individual metropolitan areas. Rates of change were calculated by ordinary least-squares linear regression. Cities with trends that are significant to a 95 percent confidence level ($p \leq 0.05$) have solid-colored circles.

For reference, Figure TD-1 shows the same type of analysis as Figure 1, but applied to daily maximum temperatures instead of daily minimum temperatures. EPA provides this additional analysis as a basis for comparison and in response to a suggestion from the external peer review of this indicator.

Figure TD-1. Heat Wave Characteristics in the United States by Decade, Based on Maximum Temperatures, 1961–2019



Data source: NOAA, 2021

Figure 3. U.S. Annual Heat Wave Index, 1895–2020

Data from the COOP data set have been used to calculate annual values for a U.S. Annual Heat Wave Index. For Figure 3, heat waves are defined as warm periods of at least four days with an average temperature (that is, averaged over all four days) exceeding the threshold for a one-in-10-year occurrence (Kunkel et al., 1999). The Annual U.S. Heat Wave Index is a frequency measure of the number of heat waves that occur each year. A complete explanation of trend analysis in the annual average heat wave index values, especially trends occurring since 1960, can be found in Appendix A, Example 2, of U.S. Climate Change Science Program (2008). Analytical procedures are described in Kunkel et al. (1999).

7. Quality Assurance and Quality Control

Data from weather stations are subject to standard quality assurance and quality control procedures, which are described in NWS manuals and publications such as the directives posted at: www.nws.noaa.gov/directives/030/030.php. NCEI also checked for data quality when calculating apparent temperature; missing or suspect data points are flagged so they can be excluded from subsequent calculations.

Cities with insufficient data from a consistent location throughout the period of record (1961–2019) were excluded from NOAA’s original analysis and from the subsequent analysis for Figures 1 and 2. These steps resulted in the exclusion of several large MSAs that would have otherwise been in the top 50 by population, as shown in Table TD-1.

Figure 3 includes many years of historical data that have been digitized from hard copies. Quality control procedures associated with digitization and other potential sources of error are discussed in Kunkel et al. (2005).

Analysis

8. Comparability Over Time and Space

Figures 1 and 2. Heat Wave Characteristics, 1961–2019

Long-term weather stations have been carefully selected to minimize changes over time in instrumentation, measuring procedures, and the exposure and location of the instruments. Although some stations have apparent temperature data back as far as the 1940s, Figures 1 and 2 begin in 1961 to maximize the number of stations with sufficient data available from a consistent location.

Analytical methods have been applied consistently to all cities and all years of data. Each MSA has a unique location-specific temperature threshold for defining a “heat wave,” but all such thresholds were calculated in the same manner with the same percentile (85th) applied, as described in Section 6.

While methods have not changed over the period of record, the built environment around any given weather station could have changed since 1961—for example, with urban and suburban growth and the corresponding reduction of vegetation and increase in impervious surfaces. These changes could have amplified the “urban heat island” effect over time in some locations. The data for this indicator have not been adjusted in any way to compensate for this effect, as Section 9 discusses in more detail.

Figure 3. U.S. Annual Heat Wave Index, 1895–2020

Similar to Figures 1 and 2, long-term weather stations have been carefully selected from the full set of all COOP stations to provide an accurate representation of the United States for the U.S. Annual Heat Wave Index (Kunkel et al., 1999). Some bias may have occurred as a result of changes over time in instrumentation, measuring procedures, and the exposure and location of the instruments.

9. Data Limitations

Factors that may impact the confidence, application, or conclusions drawn from this indicator are as follows:

1. By focusing only on the 50 largest metropolitan areas in the United States with sufficient data, this indicator provides sparse coverage of some of the less densely populated portions of the country—particularly the north-central states. This geographic gap is exacerbated by the fact that Minneapolis–St. Paul, Denver, Kansas City, and Omaha are among the large MSAs with insufficient data for analysis. Honolulu also had insufficient data, and no city in Alaska was in the

top 50 MSAs with available data, so this indicator does not provide information about Hawaii or Alaska. It does, however, include San Juan in Puerto Rico.

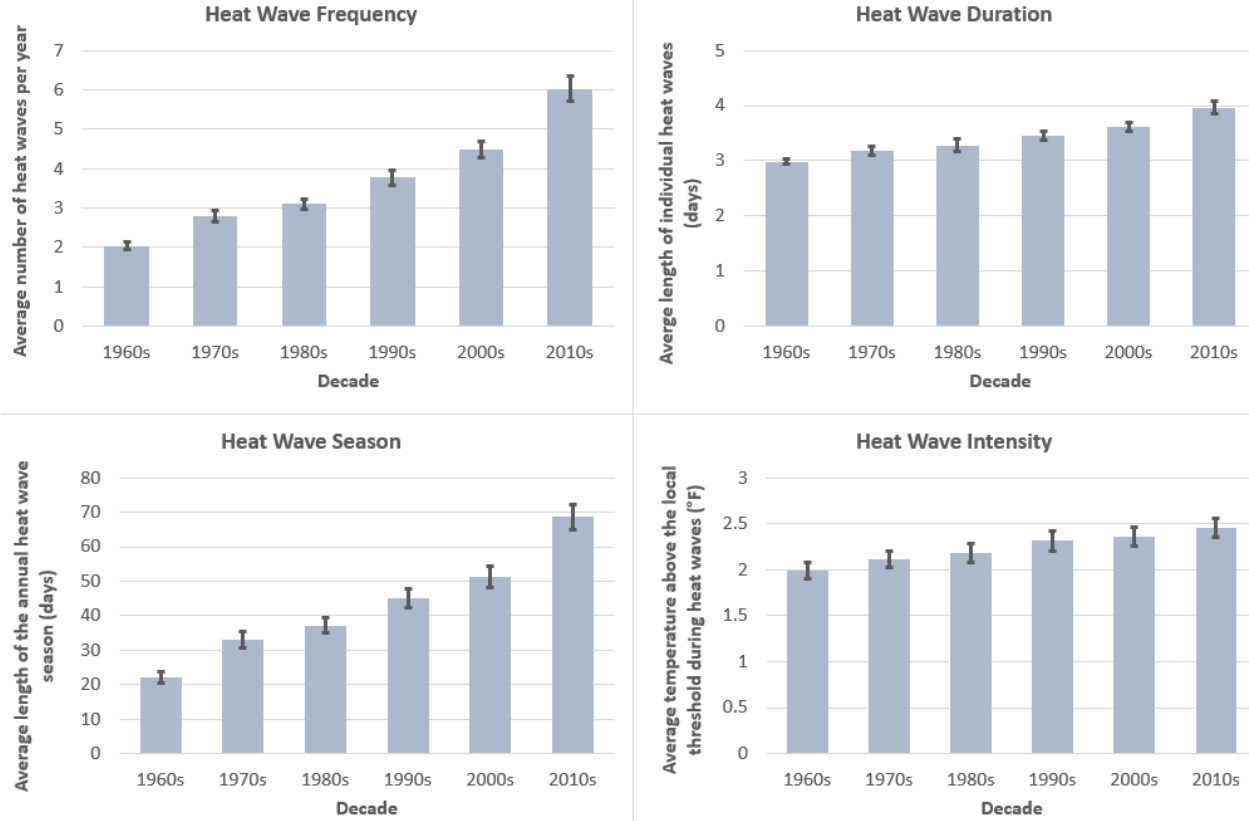
2. The “national” averages in Figure 1 are averages of the 50 cities shown in Figure 2, so they are naturally biased toward large metropolitan areas and toward parts of the country that happen to have many large metropolitan areas (e.g., the East Coast). The averages are not weighted by population, so each of the 50 MSAs in this indicator contributes equally to the overall average. Although this indicator does not exactly represent the changes in heat waves experienced by every American everywhere, it does focus on the most populous areas and reflects conditions experienced by many Americans throughout the country.
3. As cities develop, vegetation is often lost and more surfaces are paved or covered with buildings. This type of development can lead to higher temperatures—part of what is called the “urban heat island” effect. Built-up areas have higher temperatures than surrounding rural areas, especially at night. Urban growth since 1961 may have contributed to part of the increase in heat waves that this indicator shows for certain cities. This indicator does not attempt to adjust for the effects of development, because the focus is on the temperatures to which people are actually exposed, regardless of the factors that are causing these temperatures to change (i.e., regardless of the relative contributions of climate change or other influences).
4. This indicator is based on just one weather station per MSA, and the stations analyzed are all at airports, rather than in densely populated or downtown locations. Habeeb et al. (2015) describe how they compared more than 30 years of data from airport stations with downtown stations in all 50 MSAs to determine how representative the airport stations are. They found insignificant differences and concluded that “airport stations, on average, provide a reasonable proxy for temperature trends in the most centralized zones of large U.S. cities.”
5. Observer errors, such as errors in reading instruments or writing observations on the form, are present in the earlier part of this data set for Figure 3. Additionally, uncertainty may be introduced into this data set when hard copies of data are digitized. As a result of these and other factors, uncertainties in the temperature data increase as one goes back in time, particularly because there were fewer stations early in the record. NOAA does not believe, however, that these uncertainties are sufficient to undermine the fundamental trends in the data. More information about limitations of pre-1948 weather data can be found in Kunkel et al. (2005).

10. Sources of Uncertainty

Figures 1 and 2. Heat Wave Characteristics, 1961–2019

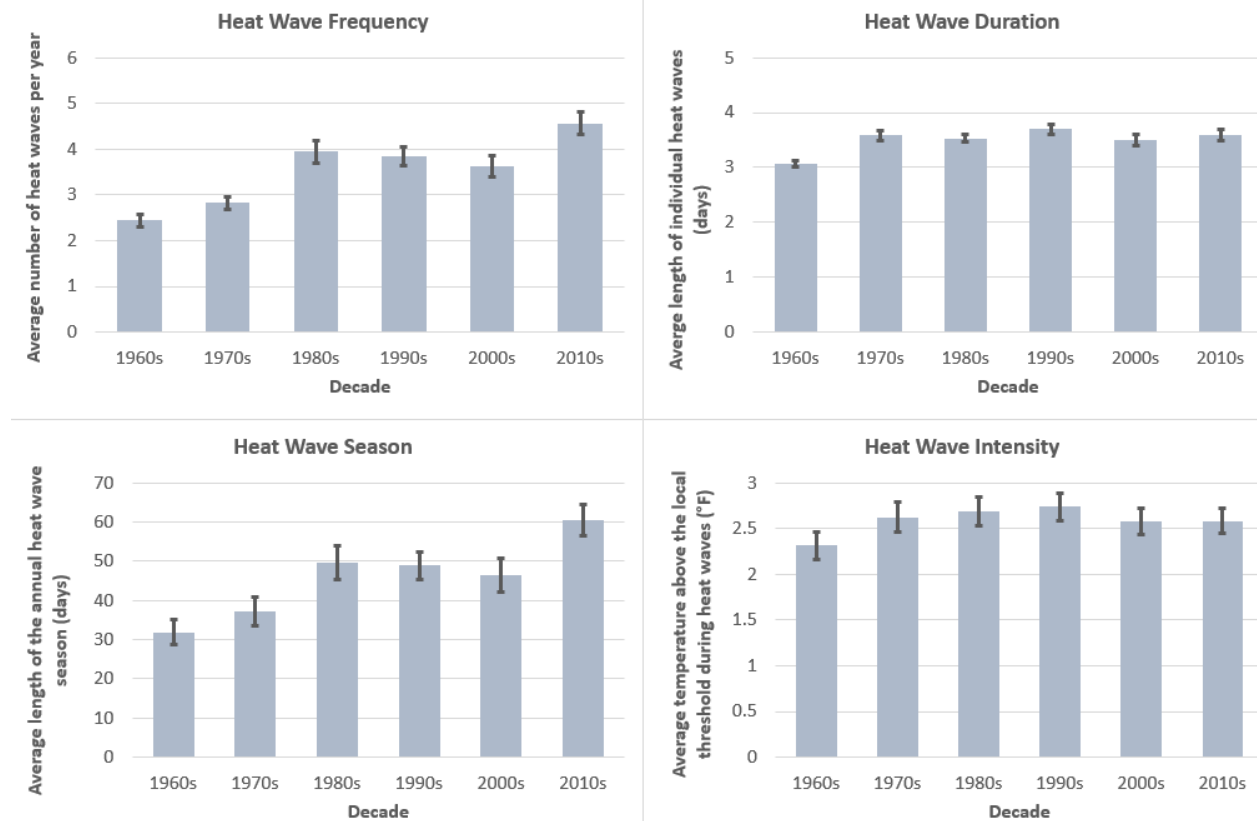
Direct temperature and humidity measurements do not typically have much uncertainty, and no serious methodological limitations have been noted. Habeeb et al. (2015) provide error bounds for each of the decadal averages in an earlier version of Figure 1, based on their analysis of data from 1961 to 2010. For the updated analysis presented in this indicator, Figure TD-2 shows the standard error for each decadal average shown in Figure 1 of the indicator. Figure TD-3 does the same for Figure TD-1. These standard errors reflect the distribution of decadal averages across the 50 cities analyzed—that is, the standard deviation of the distribution of individual city results divided by the square root of the sample size (50).

Figure TD-2. Heat Wave Characteristics in the United States by Decade, Based on Minimum Temperatures, 1961–2019, with Standard Error



Data source: NOAA, 2021

Figure TD-3. Heat Wave Characteristics in the United States by Decade, Based on Maximum Temperatures, 1961–2019, with Standard Error



Data source: NOAA, 2021

Figure 3. U.S. Annual Heat Wave Index, 1895–2020

Uncertainty may be introduced into this data set when hard copies of historical data are digitized. For this and other reasons, uncertainties in the temperature data increase as one goes back in time, particularly because there are fewer stations early in the record. NOAA does not believe, however, that these uncertainties are sufficient to undermine the fundamental trends in the data. Vose and Menne (2004) suggest that the station density in the U.S. climate network is sufficient to produce robust spatial averages.

Error estimates have been developed for certain segments of the data set, but do not appear to be available for the data set as a whole. Uncertainty measurements are not included with the publication of the U.S. Annual Heat Wave Index. Error measurements for the pre-1948 COOP data set are discussed in detail in Kunkel et al. (2005).

11. Sources of Variability

Inter-annual temperature variability results from normal year-to-year variation in weather patterns, multi-year climate cycles such as the El Niño–Southern Oscillation and Pacific Decadal Oscillation, and other factors. This indicator presents decadal averages (Figure 1) and long-term rates of change (Figure

2) to reduce the year-to-year “noise” inherent in the data. Temperature patterns also vary spatially. This indicator provides information on geographic differences by showing location-specific trends in Figure 2.

12. Statistical/Trend Analysis

Figures 1 and 2. Heat Wave Characteristics, 1961–2019

Trends in the four major heat wave characteristics (frequency, duration, season length, and intensity) were analyzed for national averages and for each individual MSA. For Figure 1 and Figure TD-1, ordinary least-squares linear regression was used to assess long-term trends in the nationally aggregated data, based on all 59 years of data. The resulting regression slopes are reported in Table TD-2 in terms of rates per decade. All results based on minimum temperature are statistically significant ($p < 0.05$), as are three of the four results based on maximum temperature.

Table TD-2. Long-Term Rates of Change for the 50-City Averages Shown in Figures 1 and TD-1

Parameter	Based on minimum temperature		Based on maximum temperature	
	National rate of change, 1961–2019	P-value	National rate of change, 1961–2019	P-value
Frequency	+0.75 heat waves per decade	< 0.001	+0.39 heat waves per decade	< 0.001
Duration	+0.21 days per decade	< 0.001	+0.10 days per decade	0.004
Season length	+8.7 days per decade	< 0.001	+5.0 days per decade	< 0.001
Intensity	+0.10°F per decade	< 0.001	+0.02°F per decade	0.53

Figure 2 uses ordinary least-squares linear regression to calculate the slope of observed trends in heat wave characteristics for each individual MSA. This analysis is based on a regression of all 59 years of data. Trends that are not statistically significant (i.e., $p \geq 0.05$) are displayed as hollow circles.

Figure 3. U.S. Annual Heat Wave Index, 1895–2020

Heat wave trends (Figure 3) are somewhat difficult to analyze because of several outlying values in data from the 1930s. Statistical methods used to analyze trends in the U.S. Annual Heat Wave Index are presented in Appendix A, Example 2, of U.S. Climate Change Science Program (2008). Despite the presence of inter-annual variability and several outlying values in the 1930s, standard statistical treatments reveal a highly statistically significant linear trend since 1960. For example, an ordinary least-squares linear regression from 1960 to 2020 gives a slope of 0.002 index units per year ($p = 0.0006$). However, the trend over the full period of record is not statistically significant.

References

Habeb, D., J. Vargo, and B. Stone, Jr. 2015. Rising heat wave trends in large U.S. cities. *Nat. Hazards* 76(3):1651–1665. doi:10.1007/s11069-014-1563-z.

Kunkel, K.E., R.A. Pielke Jr., and S. A. Changnon. 1999. Temporal fluctuations in weather and climate extremes that cause economic and human health impacts: A review. *B. Am. Meteorol. Soc.* 80:1077–1098.

Kunkel, K.E., D.R. Easterling, K. Hubbard, K. Redmond, K. Andsager, M.C. Kruk, and M.L. Spinar. 2005. Quality control of pre-1948 Cooperative Observer Network data. *J. Atmos. Ocean. Tech.* 22:1691–1705.

NOAA (National Oceanic and Atmospheric Administration). 2021. Heat stress datasets and documentation. Accessed February 2021. www.ncdc.noaa.gov/societal-impacts/heat-stress/data.

Sarofim, M.C., S. Saha, M.D. Hawkins, D.M. Mills, J. Hess, R. Horton, P. Kinney, J. Schwartz, and A. St. Juliana. 2016. Chapter 2: Temperature-related death and illness. In: *The impacts of climate change on human health in the United States: A scientific assessment*. U.S. Global Change Research Program. <https://health2016.globalchange.gov>.

Steadman, R.G. 1984. A universal scale of apparent temperature. *J. Climate Appl. Meteorol.* 23:1674–1687.

U.S. Climate Change Science Program. 2008. Synthesis and Assessment Product 3.3: Weather and climate extremes in a changing climate. www.globalchange.gov/browse/reports/sap-33-weather-and-climate-extremes-changing-climate.

USGCRP (U.S. Global Change Research Program). 2017. Climate science special report: Fourth National Climate Assessment, volume I. Wuebbles, D.J., D.W. Fahey, K.A. Hibbard, D.J. Dokken, B.C. Stewart, and T.K. Maycock (eds.). <https://science2017.globalchange.gov>. doi:10.7930/J0J964J6.

Vose, R.S., and M.J. Menne. 2004. A method to determine station density requirements for climate observing networks. *J. Climate* 17(15):2961–2971.