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The power of hourly weather data: Observed air temperature climate trends for pragmatic decision-making

Logan McLaurin[1], Sandra E. Yuter[1,2*], Kevin Burris[1¤], Matthew A. Miller[1]

1 Department of Marine, Earth, and Atmospheric Sciences, North Carolina State University, Raleigh, North Carolina, United States of America, 2 Center for Geospatial Analytics, North Carolina State University, Raleigh, North Carolina, United States of America

¤ Current address: Department of Physics and Meteorology, United States Air Force Academy, Colorado Springs, Colorado, United States of America
* seyuter@ncsu.edu

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Abstract

Analysis of hourly air temperature data from recent decades reveals trends and the degree of variability in the length of time above and below key temperature thresholds associated with the freezing point, heat stress, and energy usage. We examine hourly weather station data obtained from NOAA's Integrated Surface Database for 340 stations in the contiguous US and southern Canada from 1978 to 2023. For each station, we compute decadal trends in hours below the freezing point (0 °C, 32 °F), hours above the threshold for heat stress in animals and plants (30 °C, 86 °F), and energy usage in terms of heating and cooling degree hours (weighted deviations from 18 °C, 65 °F). Many locations in southern Canada and the north central and western US lack clear decadal trends in hours below 0 °C and have high variability in below freezing temperatures year to year. In contrast, most locations east of the Mississippi River and north of 37 °N have lost the equivalent of ∼1.5 to 2 weeks per year of temperatures below freezing compared to the early 1980s. The same northeast region shows mostly insignificant trends in hours above 30 °C. The largest gains in the number of hours above 30 °C are concentrated in the southwestern US and parts of Texas. For most locations in the northern portions of the US, the rate at which heating degree hours are lost outpaces the rate at which cooling degree hours are gained. Trends in threshold exceedance are more easily related to lived experiences than incremental changes to seasonal or annual averages. Our examination of hourly data complements assessments of historical temperature changes based on daily minimum, maximum, and average temperatures. Information on regional exceedance trends and their magnitudes can aid local climate adaption planning.

Introduction

Scientific evidence overwhelmingly supports the existence of anthropogenic climate change. Studies such as the Intergovernmental Panel on Climate Change (IPCC) Synthesis Report [1,2] and the Fifth National Climate Assessment [3] have extensively documented long-term

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changes to the climate system based on historical weather observations. Often these analyses communicate trends in terms of cumulative changes over time that are derived from daily values [4]. Definitions of what constitutes extreme heat or extreme cold are usually based on percentiles of the long-term local climatology rather than absolute values [1,2]. The Fifth National Climate Assessment includes the long-term changes in annual and seasonal average temperatures as well as the change in the number of hot days, cold days, and warm nights in the contiguous United States (CONUS) since the early 1900s [3]. While information based on daily metrics is useful and informative [5–10], it does not capture the full story.

Daily statistics do not convey the instantaneous and time-integrated impacts of weather such as precipitating storms, cloudiness changes, and air mass movements (e.g., fronts). A maximum temperature of 30 °C (86 °F) recorded for 6 hours over the course of a day will have substantially different impacts on people, animals, plants, and buildings compared to the same maximum temperature recorded for only 1 hour of a day [11–15]. The time series of air temperatures in Fig 1 for LaGuardia Airport shows a drop in temperature on 25 July 2023 between 2:00 and 3:00 PM from 30 °C to ~22 °C at the start of a rain event. In addition to precipitation, hour-by-hour timings of cloudiness and air mass movements also modify hourly surface air temperatures [16]. Short-term energy demands correlate strongly with hourly changes in temperature and daylight patterns [17,18]. A summer afternoon shower at 2:00 PM near the daily peak temperature (Fig 1) will have more of an impact on energy usage in terms of cooling degree hours than the same storm if it had occurred overnight at 9:00 PM, which is several hours after the daylight temperature peak. Trends and variability of hourly temperature data in terms of heating degree hours and cooling degree hours are pertinent inputs for forecasting future regional energy demand [19–21]. Examination of hourly data is particularly relevant for heat stress because heat stress deaths are linked to multiple hours of exposure [22], and the frequency of life-threatening heat waves is expected to increase in most climate change scenarios [23].

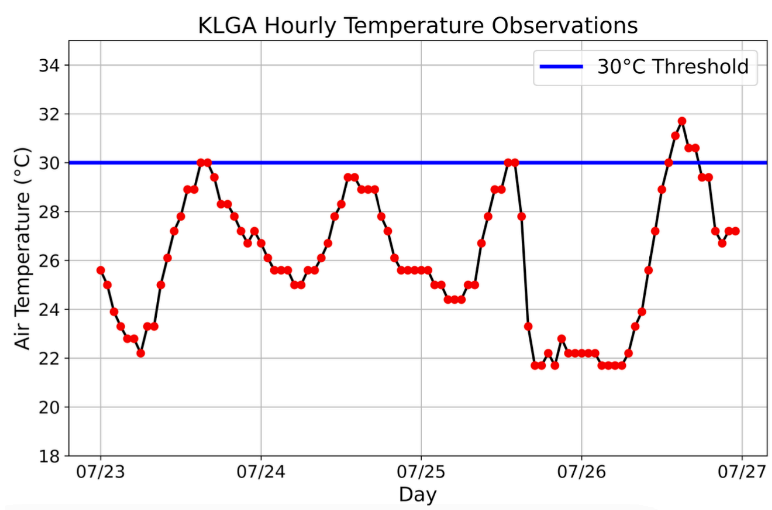

Fig 1. Hourly temperature time series for LaGuardia Airport (KLGA) in New York City from 23 July 2023 through 26 July 2023. Vertical lines are at midnight local time. The hours at or above 30 °C for each day correspond to 2, 0, 2, and 5 hours, respectively. Starting at 2:00 PM local time on 25 July 2023, afternoon thunderstorms and the subsequent passage of a cold front yielded cooling of air temperatures from 30 °C to ~22 °C, which persisted until after sunrise the next day.

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We examine hours above and below key temperature thresholds: the freezing point, heat stress, and energy usage. These temperature thresholds have clear impacts on day-to-day life. Whether the air temperature is above or below freezing is an important bifurcation in weather processes as it determines whether there is dew versus frost or rain versus snow. Freeze-thaw cycles are a major source of wear on roads and outdoor infrastructure [24]. A temperature of 30 °C (86 °F) is when people start to feel heat stress [11]. It is also a threshold for heat stress impacts on crops and domestic cattle [11–15]. Heating and cooling degree hours are based on a deviation from 18 °C (65 °F) and weighted by estimated energy usage. Our findings for temperature thresholds complement traditional methods of reporting climate changes in terms of deviations from long-term averages and the probabilities of extreme events [1–3].

The temporal scale and reporting advantages of analyzing hourly data also support broader science communication objectives. Science communicators need to continue experimenting with and refining concepts that can help engage diverse audiences with respect to climate change awareness and impacts [25,26]. We believe that distilling results from hourly historical observations has the potential to function as a useful climate change communication tool. Our goal is to provide information that can help motivate climate adaptation steps by individuals and businesses that are tailored for local and regional areas. It is often easier to convince someone of the necessity for action when information is related to their lived experiences [27,28].

Data and methods

We use the National Centers for Environmental Information's (NCEI's) Integrated Surface Database Lite (ISD-Lite) quality-controlled hourly surface weather observation data from 1978 to 2023 for locations across the CONUS and southern Canada [29,30]. Examination of the 46-year period from 1978 to 2023 is relevant for planning for anticipated changes in the next 10- to 20-year time frame [31]. While some weather stations have recorded hourly observations back to the 1940s, archival of hourly air temperatures did not become routine across the US and Canadian operational networks until the late 1970s. The ISD-Lite is a derived product representing a subset of information included in the full ISD provided by the NCEI [29,30]. The ISD contains a variety of combined surface hourly datasets from across the world. The observations are distilled into a structured attribute table after undergoing NCEI's standardized quality control methods. Air temperature is one of the parameters validated most extensively in the ISD datasets [30]. The ISD-Lite version is designed primarily for general research purposes and omits complicated flags and special observations that are part of the full ISD.

Airport weather station data

All 340 sites used for analysis correspond to the locations of airports. In the ISD and ISD-Lite, each station is characterized using multiple different identifiers (IDs) such as the United States Air Force (USAF) ID, Weather Bureau Army Navy (WBAN) ID, and the International Civil Aviation Organisation (ICAO) ID. In some cases, a single ICAO ID may be associated with more than one USAF and/or WBAN ID in the ISD-Lite. If a station is moved within an airport's grounds or upgraded, the USAF and WBAN IDs may change while the ICAO ID does not. This irregularity yields a set of encoded stations for the same ICAO ID corresponding to different time spans. In these cases, we verified the encoded stations with the same ICAO ID are within 0.03 of a degree latitude and longitude (∼3 km) of each other. We concatenated the data from these stations together in order to build the airport's complete historical hourly observation dataset from 1978 to 2023. In rare cases—likely due to a weather station being replaced—periods of overlap can exist in the historical record between encoded stations of the same ICAO ID. We resolve any instances of duplicate observations by giving priority to the encoded stations that have the most recent observations available. In addition, locations used in this analysis had to contain a country code US or CA, a latitude value less than 51 °N, recorded hourly data dating back to at least 1978, and current records of hourly observations in 2023.

For the ISD-Lite, air temperature measurements for the CONUS in the NCEI archive are encoded to a tenth of degree C. In contrast the Canadian stations, as well as the majority of stations across the world, are archived in whole degrees C.

A station's overall quantity of hourly data was evaluated in order to minimize the impact of missing data. Each year within a station record is independently evaluated. As a part of this process, observations from all leap days (29 February) are removed. If data for a particular year do not have ≥ 7500 hourly observations of the total possible 8670 hours, that year's data are discarded completely as this can skew results. If 3 or more years are consecutively discarded, the station will be excluded from the list of stations to be used in the study. A station will also be excluded if 13 or more years are discarded from the 46-year period (1978-2023). These protocols aim to preserve both the reliability and temporal continuity of trends.

We checked if each station had any extreme abnormalities or abrupt shifts within the temperature record. The only location removed based on these criteria was the Montréal-Mirabel International Airport (CYMX) in Quebec because it displayed a major, uncharacteristic shift in reporting values in 2005. Out of the 998 potential airports in the CONUS and southern Canada, 340 stations met the filtering standards required to be included in the analysis.

The hourly air temperature records for each station can be used to visualize the year-by-year air temperature distributions. Example frequency distributions of air temperature for each year over the 46-year period are shown in Fig 2 for both LaGuardia Airport (KLGA) in New York City and Hector International Airport (KFAR) in Fargo, North Dakota. As expected, due to its inland continental climate and higher latitude than New York City, the

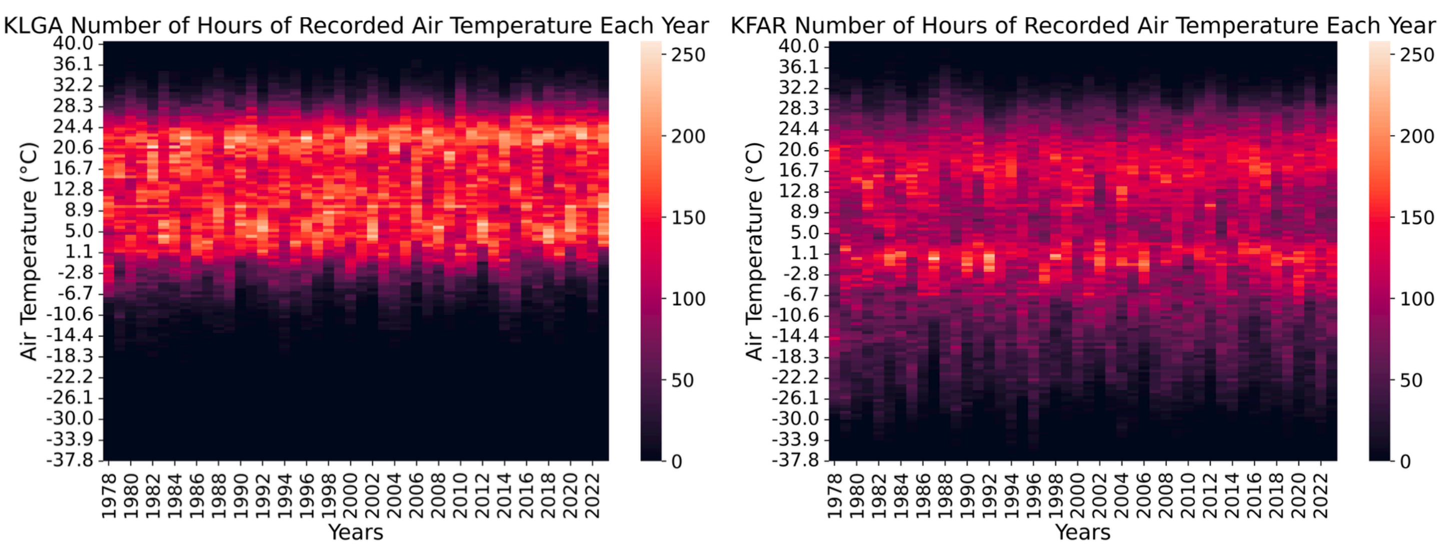

Fig 2. Hourly temperature distributions by year for (left) LaGuardia Airport (KLGA), New York City, and (right) Hector International Airport (KFAR), Fargo, North Dakota, for each year from 1978 to 2023. Data from both stations are binned at 1 °F and labeled in degree C. The Y-axis temperature scales are aligned.

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median temperature at Fargo is lower and the distribution of temperatures is wider compared to coastal New York City.

Metrics examined

We investigate how the number of hours below 0 °C (32 °F) and above 30 °C (86 °F) each year has varied between 1978 and 2023 and if there are consistent and notable trends. We use heating degree hours and cooling degree hours as a metric related to energy usage. Daily minimum, maximum, and average air temperature data have been frequently used as a proxy for energy usage in the form of heating degree days and cooling degree days [32]. A heating degree day corresponds to the energy needed to heat a building to a particular base temperature, while a cooling degree day pertains to the energy needed to cool a building to a particular base temperature. Representations of higher temporal resolution, such as heating degree hours and cooling degree hours, can be calculated in a manner similar to degree day values. Degree day values are often based on mean daily air temperatures and have been found to almost always underestimate the degree hour measurements computed directly from hourly data [33,34]. We use a base temperature (B) of 18 °C (65 °F) for our degree hour calculations as this is the widely accepted value used in other regional studies [35]. For each station, heating degree hours and cooling degree hours are directly calculated for each hourly observation in the time period. Following the methods of [34], for an air temperature measurement (T) in degree C with base temperature (B = 18 °C), the cooling degree hours (CDH) and heating degree hours (HDH) for any particular hourly observation (i) are calculated as follows:

$$CDH_i = \begin{cases} T_i - B & T_i > B \\ 0 & T_i \leq B \end{cases}$$

$$HDH_i = \begin{cases} B - T_i & T_i < B \\ 0 & T_i \geq B \end{cases}$$

Metrics are calculated for each station independently, and then regional geographic consistency is used as a check on the representativeness of the results. It may be the case that land-use changes over the decades at and near an individual airport can yield results at a particular location that are not consistent with other locations in the region.

The threshold metrics related to air temperature fall on whole number values for both degree F and degree C (0 °C = 32 °F and 30 °C = 86 °F). The threshold value used for heating and cooling degree hours of 65 °F corresponds to 18.33 °C for a quantization error of 0.33 °C for this metric.

Utilizing linear regression

Over the span of a few decades, linear trends provide a useful approximation of the observed temperature changes at a given location [36–38]. Linear trends are not designed to capture nonlinear behaviors. The quantitative values of the computed trends are closely tied to the specific observation period from 1978 to 2023.

The number of hours below 0 °C (32 °F) and above 30 °C (86 °F) as well as the number of heating degree hours and cooling degree hours are counted for each individual year. We then fit a modeled linear regression to each metric individually for each station to depict the 46-year trends (e.g., Fig 3). Linear trends are represented for air temperature thresholds in terms of hours per decade and for both degree hours metrics in terms of degree hours per

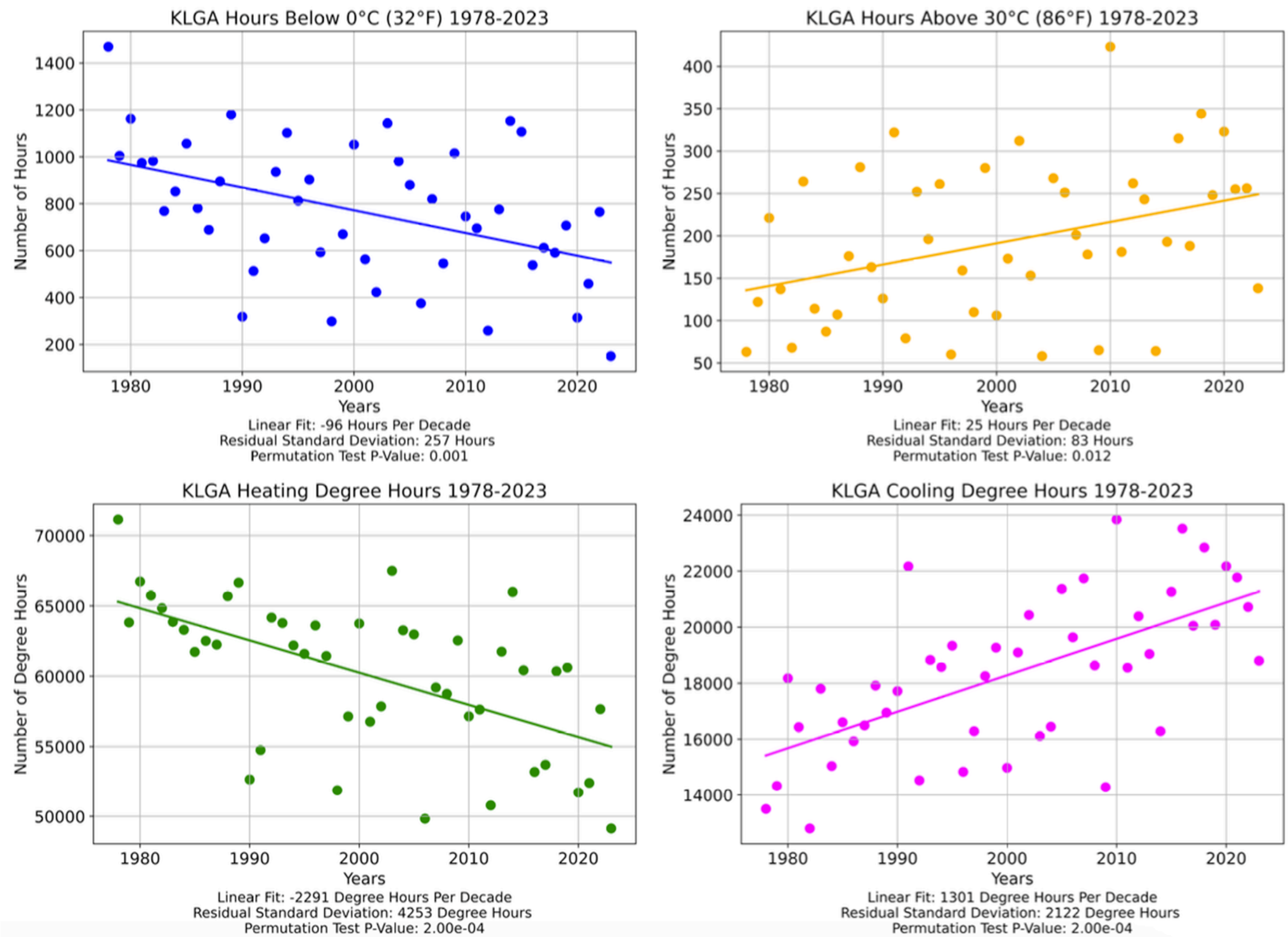

Fig 3. (Top left) The number of observations below 0 °C (32 °F) and (top right) above 30 °C (86 °F), along with (bottom left) the counts of heating degree hours and (bottom right) cooling degree hours, for LaGuardia Airport (KLGA), New York City, from 1978 to 2023. A linear regression model is used to depict the overall long-term changes for each metric. For KLGA, the linear fit equates to a loss of ~18.5 days (~446 hours) below freezing temperatures and gain of ~5 days (~112 hours) of temperatures above 30 °C (86 °F) between 1978 and 2023. The residual standard deviation describes the year-to-year variability of each metric. Residual standard deviations and p-values are shown below each subplot. The p-values for all 4 subplots are < 0.05, indicating that the trends are significant.

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decade. Stations that have a median of < 10 hours per year meeting the threshold criteria are designated as having insufficient threshold hours and a trend is not computed.

For each metric, the residual standard deviation, a measure of goodness of fit of the linear regression model, is used as a proxy for interannual variability. A greater residual standard deviation intuitively implies a greater range of threshold hours or degree hours observations across the time range relative to the linear regression model. We chose this strategy as opposed to calculating the variance of each sample set directly because the vast majority of observed distributions do not have Gaussian distributions. The residual standard deviation values are independently assessed for each air temperature threshold and degree hour metric and are not normalized.

Statistical testing to determine trend significance and variability

We examine if the magnitude of the linear trend is large enough to be notable in the sense that the observed trend is unlikely to have occurred by chance. We apply a permutation test (also known as a randomization test or a form of Monte Carlo test) in order to assess the significance of the linear regression trend. Permutation tests have been commonly used as a method of statistical hypothesis testing that can be adapted for a variety of experimental applications [39–42]. We follow established methods for permutation testing [40,41]. The null hypothesis is that the linear regression trend in hours per decade calculated is attributable to random variation of the observed distribution over time. The distribution is permuted by shuffling the samples of the observed dataset without replacement, representing a different arrangement of the original sample of observations [40]. The test statistic, the linear regression trend, is then calculated for each permutation. This process is repeated to generate 10,000 permutations of the potential 46! combinations possible in order to compile the permutation distribution of potential trend magnitudes. The observed test statistic is then compared to the distribution of permutation tests. The null hypothesis is rejected, and the trend is marked significant if the observed trend falls within either extreme 5th percentile of the permutation distribution (standard two-tailed p-value of ≤ 0.05). Based on the 46 observations in each station sample, the 0.05 threshold would be classified as a fair significance for this sample size [43]. By this criterion, the metrics illustrated for LaGuardia Airport (KLGA) in Fig 3 are all statistically significant trends. In comparison, the trends for Pierre Regional Airport (KPIR) in South Dakota (Fig 4) are not significant despite illustrating nonzero magnitudes.

There are a multitude of advantages that support the use of the permutation test for our specific application. This test makes no assumptions regarding the underlying population distribution of the data when producing samples or evaluating the trend statistic [40,41]. The occasional presence of outliers in the sample distributions is mitigated in their impact relative to the statistic being tested under the methodology of the permutation test [39,40]. Furthermore, permutation tests have the ability to yield powerful statistical results for small sample sizes, which applies to the 46-year time range analyzed [39,42]. Under the null hypothesis stated, the shuffling component assumes that any observation from the distribution can randomly take place during any year between 1978 and 2023. While randomness is not characteristic of actual air temperature time series that include year-to-year dependencies based on short-term internal climate variability [44–47], the permutation test adequately serves the purpose of testing the significance of the simplified linear regression trend.

Results

Information on where there are significant trends and where year-to-year variability is high is helpful in understanding how warming climate manifests region by region. Geographic maps of the variability of historical air temperature changes are usually not included in materials designed for policymakers [3]. Information on trends and variability for each weather station reveals regional spatial consistency for the temperature thresholds (Fig 5) and degree hours (Fig 6). The study area is divided into 4 approximately equal-area quadrants by lines along 37 °N and the 98 °W to facilitate comparisons among regions.

Freezing point and heat stress thresholds

In the winter season, large, significant negative trends in hours below 0 °C (32 °F) are clustered in the northeastern portion of the CONUS (Fig 5) (82 out of 137 stations). For locations east of the Mississippi River and north of 37 °N, these trends correspond with a decrease

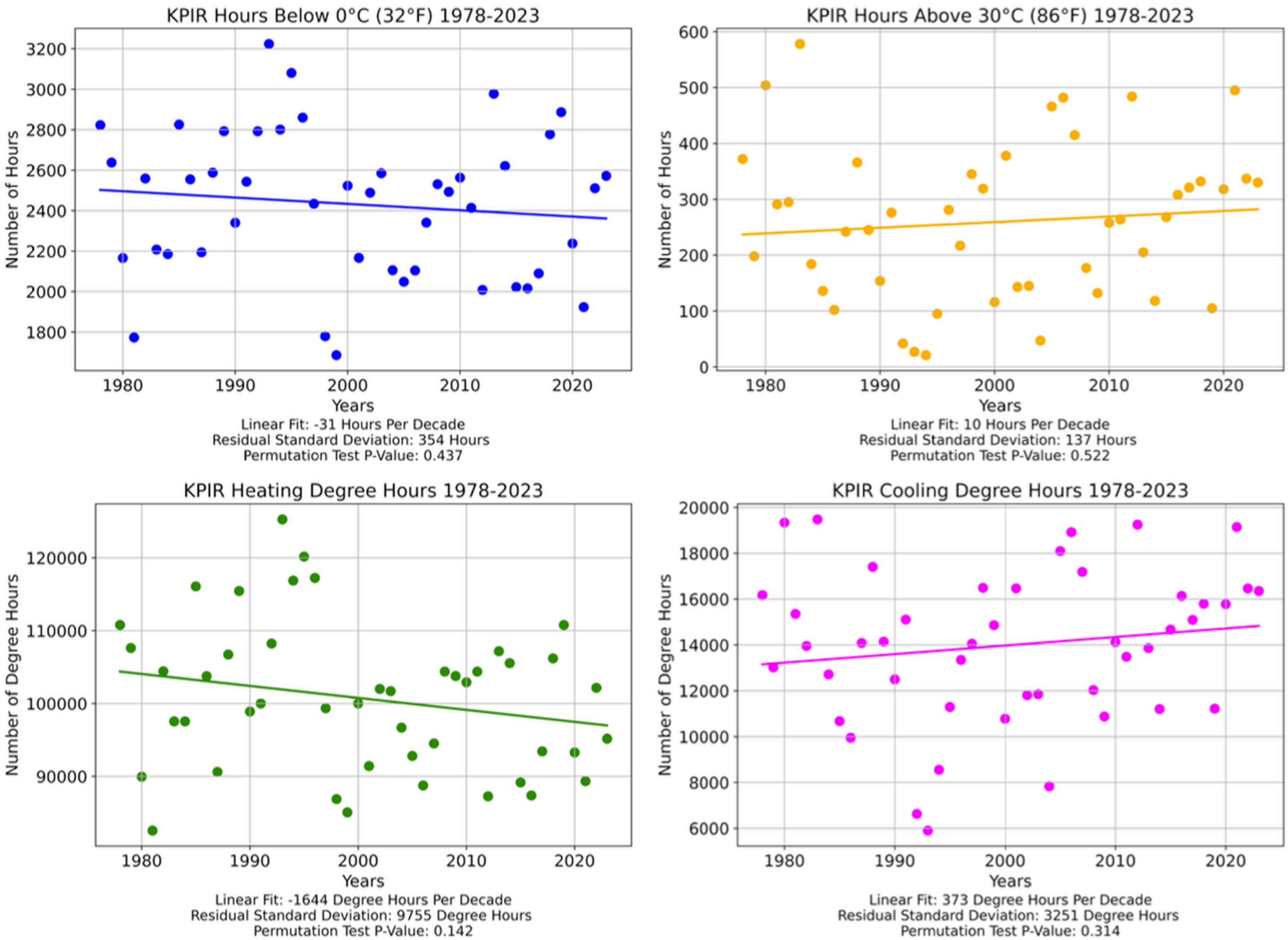

Fig 4. (Top left) The number of observations below 0 °C (32 °F) and (top right) above 30 °C (86 °F), along with (bottom left) the counts of heating degree hours and (bottom right) cooling degree hours, for Pierre Regional Airport (KPIR), South Dakota, from 1978 to 2023. A linear regression model is used to depict the overall long-term changes for each metric. The residual standard deviation describes the year-to-year variability of each metric. Despite demonstrating nonzero trend magnitudes, particularly in the winter season, these trends are insignificant due to the overall high variability. Residual standard deviations and p-values are shown below each subplot. The p-values for all 4 subplots are > 0.05, indicating that the trends are not significant.

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of ~1.5 to 2 weeks of hours below freezing since the early 1980s. In the northwest quadrant, most locations (68 out of 82 stations) in Minnesota, Iowa, North Dakota, South Dakota, Montana, Wyoming, Washington, and southern Canada have high year-to-year variability without a significant trend. As expected, there are smaller losses in number of hours below 0 °C (32 °F) in the southern US states as compared to more northern locations because there are fewer hours below 0 °C (32 °F) in southern locations overall. While the magnitudes were low, 65% of stations in the southeast region (58 of 89 stations) demonstrated significant negative trends in hours below 0 °C (32 °F).

In the summer season, almost all locations west of the Rocky Mountains have significant positive trends in the hours above 30 °C (86 °F) (Fig 5). Specifically, 81% of stations in the southwest region (26 of 32 stations) feature significant positive trends in hours above 30 °C

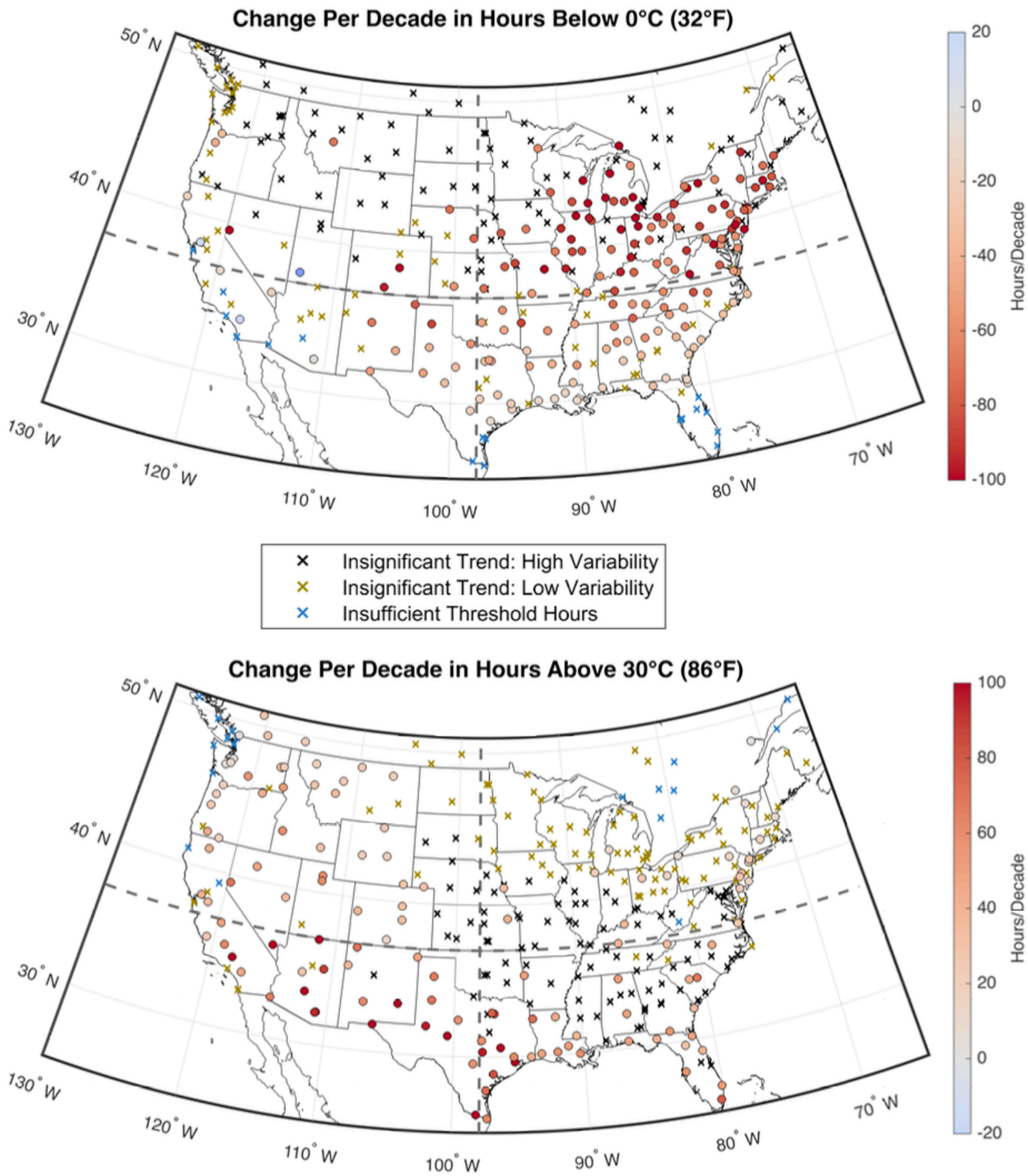

Fig 5. Changes in (top) the number of hours below 0 °C (32 °F) and (bottom) number of hours above 30 °C (86 °F) from 1978 to 2023 for 340 airports across the CONUS and southern Canada. Dashed gray lines at 37 °N and 98 °W separate geographic quadrants representing the northeast, northwest, southeast, and southwest regions of the CONUS and southern Canada study area. Statistically significant trends in units of hours per decade are shown in colored circles. Warming trends are denoted in shades of red and orange for both maps. Insignificant trends are divided into categories of high variability (residual standard deviation ≥ median residual standard deviation) or low variability (residual standard deviation < median residual standard deviation). Stations with insufficient threshold hours passed all filtering procedures but have a median of < 10 threshold hours each year for the corresponding metric across the 46-year period. Basemap and country boundaries were plotted using the Mapping Toolbox for MATLAB [48]. The public domain base layer shapefiles are from Natural Earth.

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(86 °F). The highest magnitude summer warming trends are in southern California, Nevada, Arizona, New Mexico, Texas, Louisiana, and Florida. In these locations, the occurrence of temperatures above 30 °C (86 °F) increased by ~1.5 weeks' worth of hours since the late

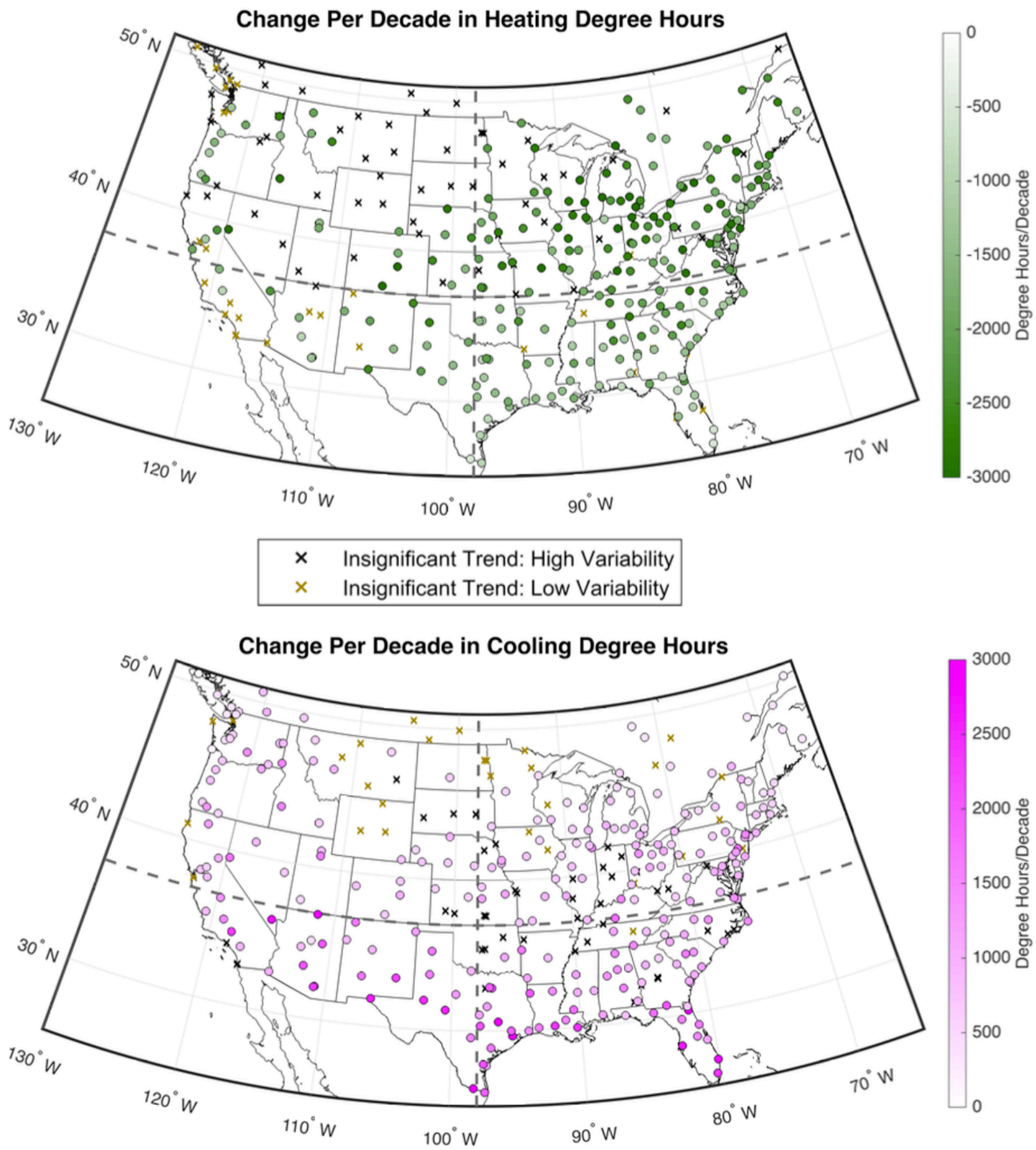

Fig 6. Changes in (top) the number of heating degree hours and (bottom) cooling degree hours from 1978 to 2023 for 340 airports across the CONUS and southern Canada. Statistically significant regression trends are colored by magnitude in terms of degree hours per decade. Dashed gray lines at 37 °N and 98 °W separate geographic quadrants representing the northeast, northwest, southeast, and southwest regions of the CONUS and southern Canada study area. Stations without significant trends are divided into categories of high variability (residual standard deviation ≥ median residual standard deviation) or low variability (residual standard deviation < median residual standard deviation). Basemap and country boundaries as in Fig 5.

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1970s. Many stations in the central CONUS (Nebraska, Kansas, Missouri, Illinois, Indiana, Oklahoma, and Arkansas) indicate high variability and no significant trends in hours above 30 °C.

Heating degree hours and cooling degree hours

The regional analyses of both degree hour variables (Fig 6) complement the findings illustrated in the air temperature threshold maps (Fig 5). Apart from the midwestern United

States, an overwhelming majority of stations have significant decreases in heating degree hours (proxy for decreasing energy usage trends in the winter) and increases in cooling degree hours (proxy for increasing energy usage trends in the summer). Heating degree hours and cooling degree hours relate to likely changes in the relative energy use not accounting for any changes in technology, insulation, and building codes. The greatest decreases in the amount of heating degree hours in the winter have occurred in states in the mid-Atlantic and south of the Great Lakes. The greatest increases in cooling degree hours in the summer have occurred in Florida, Louisiana, southeastern Texas, and portions of the southwest. In summer, locations near the geographic center of the CONUS (e.g., Oklahoma, Kansas, Nebraska, South Dakota) often have high variability in cooling degree hours without significant trends.

We compared statistics for cooling degree hours versus cooling degree days and heating degree hours versus heating degree days (not shown). In terms of the significance of the trends, there was not much difference for heating, but using cooling degree hours rather than days increased the number of stations with significant trends by 31.

Winter warming often offsets summer warming in terms of the degree hour energy use proxy (Fig 7). The 185 stations that have both significant heating and cooling degree hour trends are divided into 4 quadrants using their position relative to 37 °N and 98 °W. For all stations in the northwest quadrant and most in the northeast quadrant, the reduction in heating degree hours in winter is outpacing the increase in cooling degree hours in summer (Fig 7). This also holds true for approximately half of all stations in the southern half of the CONUS. In winter, locations with high variability in heating degree hours without significant trends occur in southern Canada, Montana, Wyoming, the Dakotas, and high-altitude locations in western states.

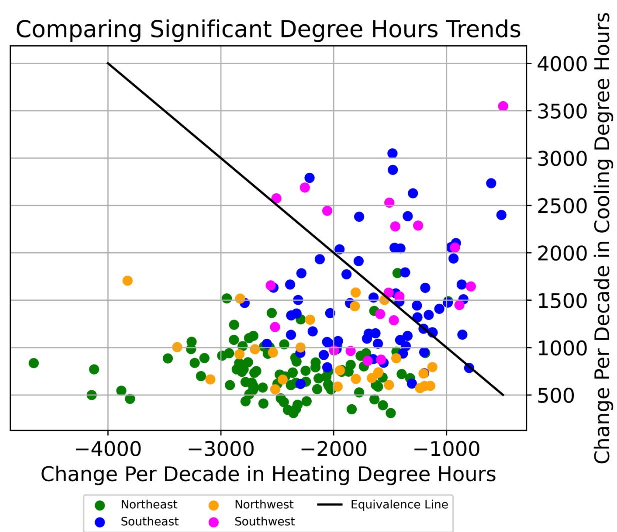

Fig 7. Trends in heating degree hours compared to trends in cooling degree hours for subset of 214 stations that have both significant heating degree hours and cooling degree hours trends. This subset of stations is further divided into geographic quadrants separated by 37 °N and 98 °W, representing the northeast, northwest, southeast, and southwest regions of the CONUS and southern Canada study area. For all northwest stations (orange), almost all northeast stations (green), and approximately half of both southern regions (cyan and pink), the reduction in energy usage (heating degree hours) in winter outpaces the increase in energy usage (cooling degree hours) in summer.

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Variability

Information on year-to-year variability is extremely relevant for climate change adaptation and in some cases may be more relevant than if a notable trend is present. More variability in recent historical conditions is likely to continue into the near future, yielding a wider range of outcomes that communities need to prepare for than if a notable trend was present. We can obtain information on the nature of variability for each station by examining the relationship between trend magnitudes and the residual standard deviations (Fig 8). Smaller residual standard deviations imply better linear trend fits as compared to higher residual standard deviations.

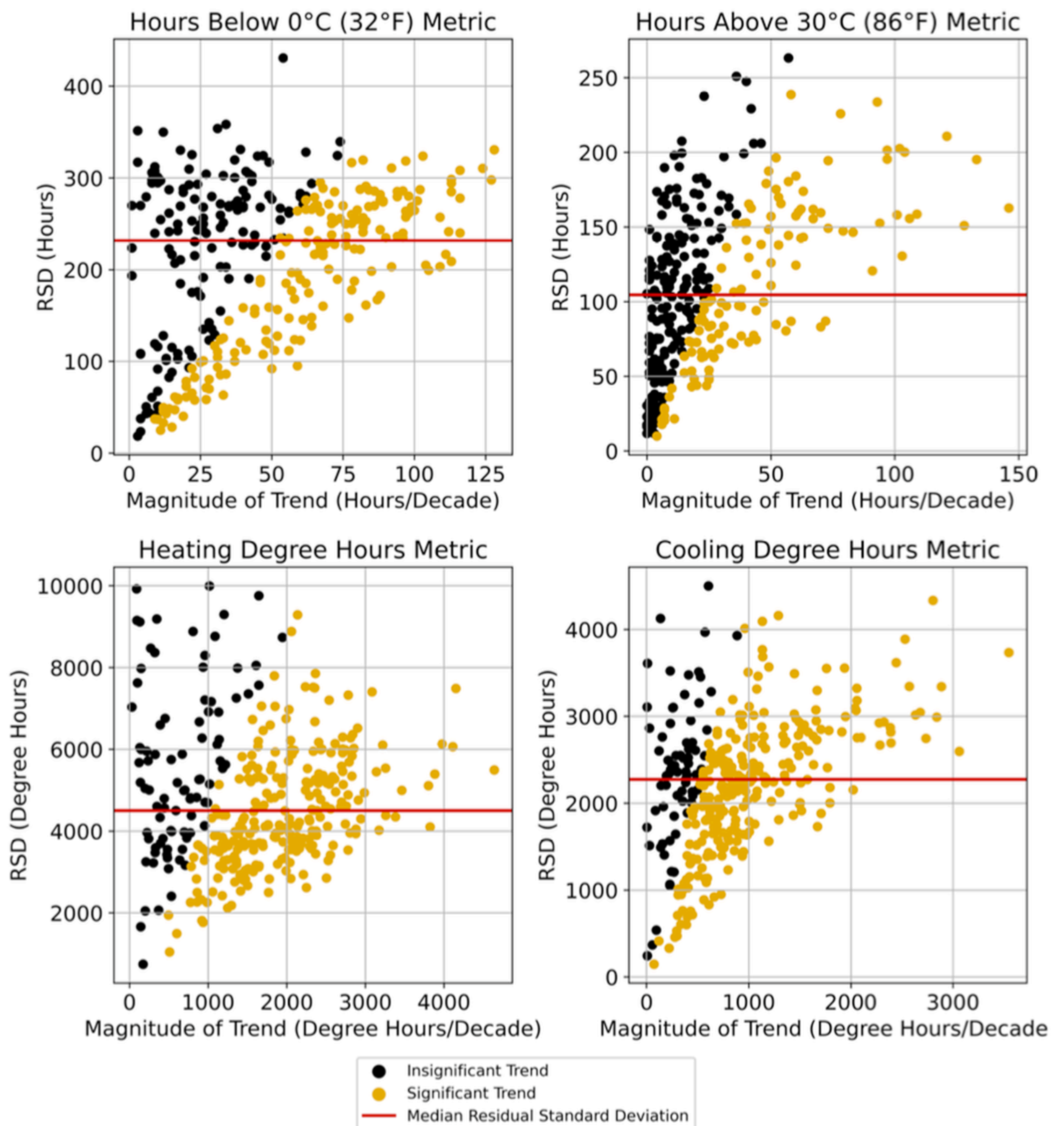

Fig 8. Trend magnitude and residual standard deviation for stations with significant trends (orange dots) and with insignificant trends (black dots) as determined by the permutation test. Median residual standard deviation is shown by the red line in each panel. (top left) Hours below 0 °C (32 °F), (top right) hours above 30 °C (86 °F), (bottom left) heating degree hours, and (bottom right) cooling degree hours.

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For the stations with significant trends, the variability is more organized along the trend line. Larger magnitude trends tend to be associated with higher variability as measured by the residual standard deviation (Fig 8). Some stations categorized with insignificant trends by the permutation test have weak trends with high variability, while others have weak trends with low variability (black dots in Fig 8). In Figs 5 and 6, stations with insignificant trends and with a residual standard deviation greater than or equal to the median are classified as high variability, and those with a residual standard deviation less than the median are classified as low variability. Stations marked insignificant with low variability are likely to exhibit a weak trend magnitude.

An insignificant trend with high variability may or may not imply any changes over time. For each of the four metrics in Fig 8, the dividing line between stations marked with a significant trend and those marked with an insignificant trend has an approximate slope of 4:1. This is likely dependent in part on the specific number of observations being shuffled (46 years) within the permutation test that marks significance. Hence, the specific stations falling along either side of the geographic borders of insignificant and significant trends will vary slightly depending on the length and specific years of the historical period examined (Figs 5 and 6).

Discussion

Summary of findings

Analysis of hourly temperature variations improves the ability to resolve and evaluate the impacts of weather and climate change that cannot be readily captured by daily mean or daily minimum and maximum values [49,50]. Hourly data provides a higher degree of granularity that can support analyses of diurnal and short episodic temporal variations, which daily data cannot provide. We examine several societally relevant metrics based on hourly temperature data: hours below 0 °C (32 °F), hours above 30 °C (86 °F), heating degree hours, and cooling degree hours. We calculate trends based on linear regression and assess their significance based on a permutation test. Decadal statistics that show spatially consistent values among nearby stations increase confidence in the findings. It is simpler to plan and justify adaptation strategies for locations with clear trends. Stations with low variability and without significant trends experienced small changes in recent decades. It is difficult to anticipate likely near-future changes for stations with high variability and without significant trends. High year-to-year temperature variability brings the potential for reserve energy margins to be frequently stretched beyond the anticipated average seasonal peak capacity during long periods of exceptionally hot or cold temperatures.

Analysis of historical hourly weather station observations in the CONUS and southern Canada from 1978 to 2023 reveals the variability and trends of recent air temperature changes. This detailed hourly analysis complements previous work based on the daily temperature record [1–3]. We add value by providing information on temperature threshold variability and significance of trends. The key findings of this analysis are:

- Many stations in southern Canada and the north-central US (North Dakota, South Dakota, Minnesota, Wisconsin, Iowa, Wyoming, and Nebraska) lack clear decadal trends in hours below 0 °C and above 30 °C.
- Most stations east of the Mississippi River and north of 37 °N have lost the equivalent of ~1.5 to 2 weeks temperatures below 0 °C. These locations also typically have smaller magnitude trends of warming in summer than in winter.

- Multiple stations in Arizona, New Mexico, and parts of southern Nevada, southern California, and southern Texas have gained the equivalent of ∼1.5 weeks of temperatures higher than 30 °C, a threshold at which agricultural crops and animals start to experience heat stress symptoms.
- Nearly all stations in the northeast and northwest portions of the CONUS have lost more heating degree hours than gained cooling degree hours, which suggests a net decrease in annual energy use based on this proxy.

Hourly temperatures at any given location are influenced by multiple interacting factors, including characteristics of synoptic scale waves of high and low pressure, storm tracks, cloudiness, precipitation patterns, soil moisture, surface type, and distance to large bodies of water [16]. Interannual climate variability [44–47,51] can also modulate regional distributions of hourly temperatures on annual timescales directly or via teleconnections. Future work is recommended to diagnose the relative importance of these factors in explaining the historical results presented in this study. Recent work [52,53] using machine learning and explainable artificial intelligence to distinguish between climate change trends and internal climate variability are approaches that may be fruitful.

For weather stations adjacent to nearby cities, it is likely that our four hourly metrics are being impacted in part by the warming induced by urban expansion since 1978 [54]. The urban heat island effect increases the risks of heat stress and heat-related illnesses for those living in urban areas [55,56]. For example, [57] found that the urban heat island around New York City impacts the local mesoscale weather by locally increasing temperatures by ∼4 °C during the summer and ∼3 °C during the winter.

Anthropogenic climate change and and surface cover changes, including urban heat island and ecosystem changes such as replacement of forest by agriculture [58], tend to accumulate and evolve over time. The observed trends derived from the hourly data encompass the combined impacts of these factors. As a consequence, the year-to-year observations within the time series of each metric for each station are not assumed to be independent of one another. Some details of weather station siting may yield large discrepancies among geographically adjacent locations. We emphasize the more robust findings that have regional geographic coherence.

Applications

This study's framework of hourly temperature threshold analysis enables the improved detection of subtle but ecologically significant shifts that daily data might overlook, thereby strengthening the capacity to anticipate and adapt to these ecosystem and societal impacts. Examination of hourly air temperature data is potentially useful for ascribing shifts in ecological patterns and organism behaviors, changes in snowpack volume, and growing season duration. The sharp decreases in the number of hours below freezing have far-ranging implications for ecosystems across the eastern regions of the CONUS. Over the past few decades, both snowfall accumulation totals and snowfall depths have decreased in conjunction with warmer winters in the upper midwest and northeast of the CONUS [59]. The degree to which insect populations survive the winter is related to both snowpack and temperature changes [60]. The increased length of the growing season by 10 to 20 days in many regions of the CONUS is primarily due to an earlier onset of warmer temperatures and a decreased amount of freezing temperatures during the seasonal transition from winter to spring [61].

Communicating trends and variability is crucial for aiding the public's understanding of climate [62]. A given winter may not always be warmer than the one preceding it. Many people who have lived in a given location for several decades recognize that there are more warm spells in the winter than there used to be. Translating this perception into the loss of 1.5 weeks of temperatures below freezing for the northeast CONUS makes it more tangible than reporting that average winter season temperatures have increased by 1 °F to 2 °F from 2002 to 2021 as compared to 1901 to 1960 [3]. How the human mind processes the temporal aspects of a changing climate differs for shorter versus longer periods of time [63]. Effective data storytelling and methods that connect with the audience's personal experiences can help to reframe issues to make them more relevant and actionable [64] and can further engage the public with these issues [25,26].

Information on impacts based on hourly data analysis of temperature threshold metrics helps to connect lived experience to quantitative values that can be used by policymakers, businesses, and homeowners to justify and plan climate adaptations such as targeted modifications to infrastructure. For example, local adaptation strategies to decrease the ambient temperatures within and near cities are crucial for limiting heat stress as well as summer season energy costs and need to be tailored for each location [65]. We believe that these types of analyses could serve as part of a science communication strategy to engage the public and decision-makers and motivate pragmatic climate action.

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Author contributions

Conceptualization: Logan McLaurin, Sandra Yuter.

Data curation: Logan McLaurin, Kevin Burris, Matthew A. Miller.

Formal analysis: Logan McLaurin, Sandra Yuter.

Funding acquisition: Sandra Yuter.

Investigation: Logan McLaurin, Sandra Yuter.

Methodology: Logan McLaurin, Sandra Yuter, Kevin Burris, Matthew A. Miller.

Project administration: Sandra Yuter.

Resources: Matthew A. Miller.

Software: Logan McLaurin, Kevin Burris, Matthew A. Miller.

Supervision: Sandra Yuter, Matthew A. Miller.

Validation: Logan McLaurin.

Visualization: Logan McLaurin, Sandra Yuter.

Writing – original draft: Logan McLaurin, Sandra Yuter.

Writing – review & editing: Logan McLaurin, Sandra Yuter, Kevin Burris, Matthew A. Miller.

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