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

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Abstract

People, animals, and plants experience air temperature on an hourly basis. Hourly data can be mined to derive information that is more easily related to lived experiences in comparison to incremental changes to seasonal averages. We analyze hourly weather station data obtained from NOAA's Integrated Surface Dataset for 340 stations in the contiguous United States and southern Canada from 1978 to 2023. For each station, we compute linear regression trends in the change per decade in hours below 0°C (32°F), hours above 30°C (86°F), and energy usage in terms of heating and cooling degree hours. Many locations in southern Canada and the north central US lack clear decadal trends in hours above 30°C (86°F) and below 0°C (32°F). Most locations east of the Mississippi River and north of 37° latitude have lost the equivalent of ∼1.5 to 2 weeks per year of temperatures below freezing compared to the early 1980s. The largest gains in the number of hours above 30°C (86°F) 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 suggesting a net yearly energy demand reduction.

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 evidence for long-term changes to the climate system based upon historical weather observations. Often these analyses communicate trends in terms of cumulative changes over time that are derived from *daily values* [4]. Examples from the Fifth National Climate Assessment include 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, it does not capture the full story. Daily statistics do not convey the instantaneous and time-integrated impacts of weather. A maximum temperature of 30°C (86°F) recorded for six 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 one hour of a day. The onset of precipitation can dramatically impact air temperature conditions and can be resolved by hourly data. In addition to precipitation, hour-by-hour timing of cloudiness and air mass movements also modify hourly surface air temperatures (e.g., Fig. 1). Consecutive days often have different temperature variations, and

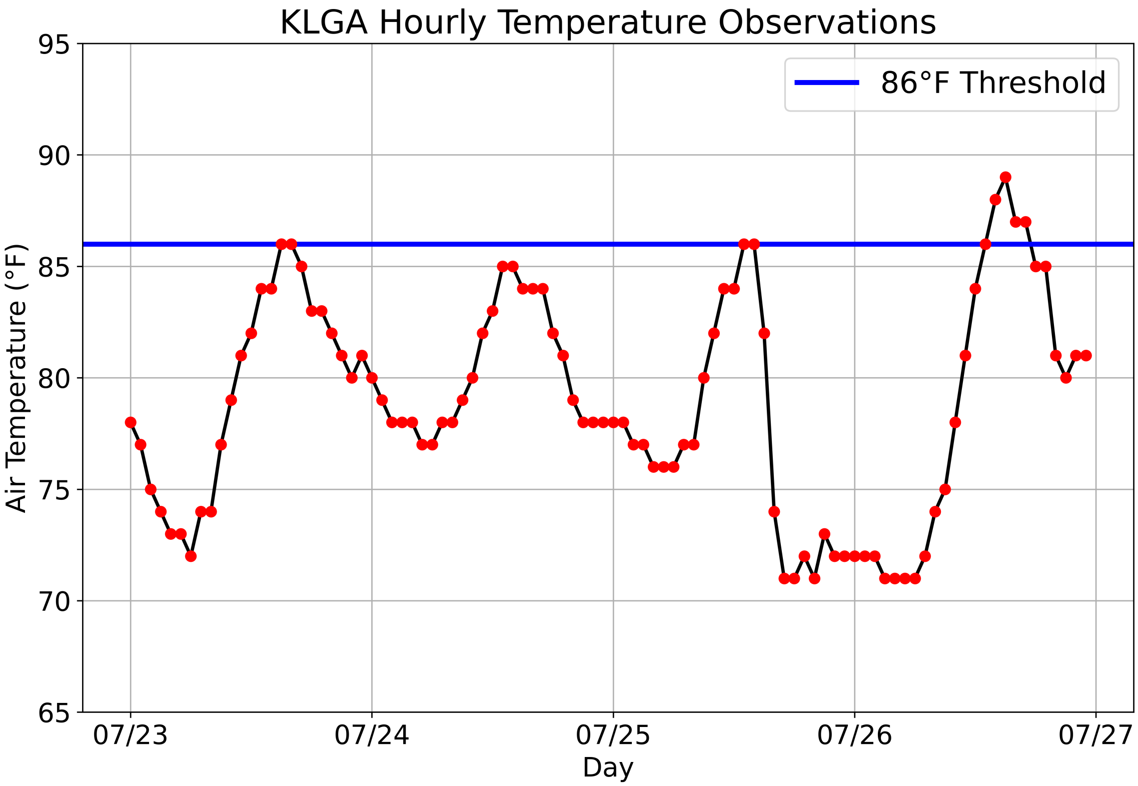

Fig 1. Hourly temperature time series for LaGuardia Airport (KLGA) from July 23, 2023 through July 26, 2023. Vertical lines at midnight local time. The hours at or above 86°F for each day correspond to 2, 0, 2, and 5 hours respectively. During the mid-afternoon on July 26, a cold front and afternoon thunderstorms yielded sudden cooling of air temperatures from 86°F to ∼71°F which persisted until after sunrise the next day.

thus, have different impacts. An afternoon shower at 2:00 PM, such as on July 25, 2023 at LaGuardia Airport, will have more of an impact on energy usage than the same storm if it had occurred at 9:00 PM (Fig. 1).

We use the National Centers for Environmental Information's (NCEI) Integrated Surface Database Lite (ISD-Lite) quality-controlled hourly surface weather observation data from 1978 to 2023 for locations across CONUS and southern Canada [5, 6]. Analysis of hourly temperature variations improves the ability to resolve and analyze the impacts of weather and climate change that cannot be captured by daily mean or daily minimum and maximum values [7, 8]. This is particularly important with regards to heat stress as the frequency of life-threatening heat waves is expected to increase in most climate change scenarios [9]. Trends and variability of hourly temperature data in terms of heating degree hours and cooling degree hours is a pertinent input for forecasting future regional energy demand [10–12].

Our goal is to provide information that can motivate climate adaptation steps by individuals and businesses that is 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 [13, 14]. To this end, we focus on hours above and below particular temperature thresholds. We have selected thresholds related to 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 [15]. A temperature of 30°C (86°F) is when people start to feel heat stress [16]. It is also a threshold for heat stress impacts on crops and domestic cattle [16–20]. Heating and cooling degree hours are based on a deviations 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].

Science communicators need to continue experimenting with and refining concepts that can help engage diverse audiences with respect to climate change awareness and impacts [21, 22]. We believe that distilling results from hourly historical observations have the potential to function as a useful climate change communication tool.

Data and Methods

Hourly air temperature data is analyzed for the 46-year period from 1978 to 2023. 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 database is a derived product representing a subset of information included in the full Integrated Surface Database (ISD) provided by the NCEI [5, 6]. 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 data sets [6]. 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 data set.

Airport Weather Station Data

All sites used for analysis correspond to the locations of airports. In the ISD and ISD-Lite system, each station is characterized using multiple different identifiers such as the United States Air Force ID (USAF), Weather Bureau Army Navy ID (WBAN), and the International Civil Aviation Organisation ID (ICAO). In some cases, a single ICAO identifier may be associated with more than one USAF and/or WBAN identifier in the ISD-Lite dataset. If a station is moved within an airport's grounds or upgraded, the USAF and WBAN identifiers may change while the ICAO identifier does not. This irregularity yields a set of encoded stations for the same ICAO corresponding to different time spans. In these cases, we verify the encoded stations with the same ICAO are within 0.03 of a degree latitude and degree longitude (∼3 km) of each other. We concatenate 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. We resolve any instances of duplicate observations by giving priority to the encoded stations that have the most recent observations available. In addition to the location requirements of the encoded stations discussed above, several addition criteria are applied to select the set of stations used in this study. Locations must 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 dataset, air temperature measurements for CONUS are encoded in whole degrees Fahrenheit which we then convert to the nearest tenth of a degree Celsius. The encoded resolution of the air temperature observations for the stations in Canada as well as the majority of stations across the world are in whole degrees Celsius. For this analysis, all air temperature observations are binned to the nearest whole degree Celsius. While this process may lead to a slight quantization error, the difference is assumed to be negligible relative to the climatological trends of interest. Conversion to the Celsius scale for the US stations facilitates coherence between the analysis of the CONUS stations and the rest of the world. For each location and each year, the air temperature observations are aggregated into a frequency distribution with 1-degree Celsius bins. Example frequency distributions of air temperature for each year over the 46-year study period are shown in Figure 2 for both LaGuardia Airport (KLGA) in New York City and Ottawa International

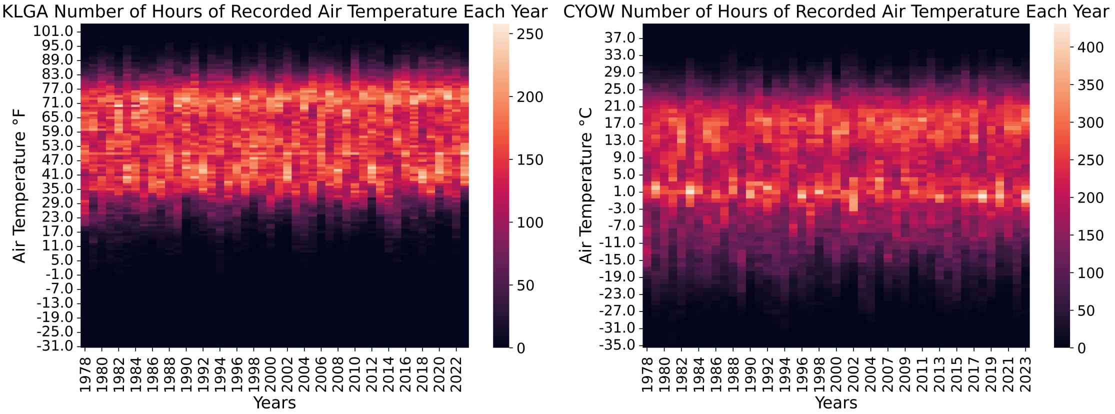

Fig 2. Hourly temperature distributions by year for (left) LaGuardia Airport (KLGA), New York, USA and (right) Ottawa International Airport (CYOW), Ontario, Canada for each year from 1978-2023. For visualization purposes, the temperature bins for each station are shown in the units in which they are recorded (°F for KLGA and °C for CYOW). To facilitate comparisons across the figure, the Y-axis temperature scales are lined up such that the maximum and minimum temperatures align (104°F = 40°C and -31°F = -35°C).

Airport (CYOW) in Ottawa, Ontario. As expected, due to its higher latitude and inland continental climate, the distribution is shifted to colder temperatures and there is a longer tail of very low temperatures for Ottawa as compared to coastal New York City.

A station's overall quantity of hourly data is 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 does not have $\geq$ 7500 hourly observations of the total possible 8670 hours, that year's data is discarded completely as this can skew results depending on whether or not large chunks of time within a given year are missing. If three 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 for these problems was the airport CYMX from Montréal, Quebec, as it displayed a major, uncharacteristic shift in reporting values in 2005. Out of the 998 potential airports in the CONUS and southern Canada geographic region, 340 stations met the filtering standards required in order to be included in the analysis.

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 [23]. 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 [24, 25]. 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 [26]. 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 Guttman and Lehman (1992), for an air temperature measurement T with base temperature B, 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.

Utilizing Linear Regression

Over spans of a few decades, linear trends provide a useful approximation of the observed temperature changes at a given location [27–29]. The 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 decade. Stations that have a median of $\leq$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 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 [30–33]. We follow established methods for permutation testing [31, 32]. 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 [31]. 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 less than or equal to .05). Based upon the

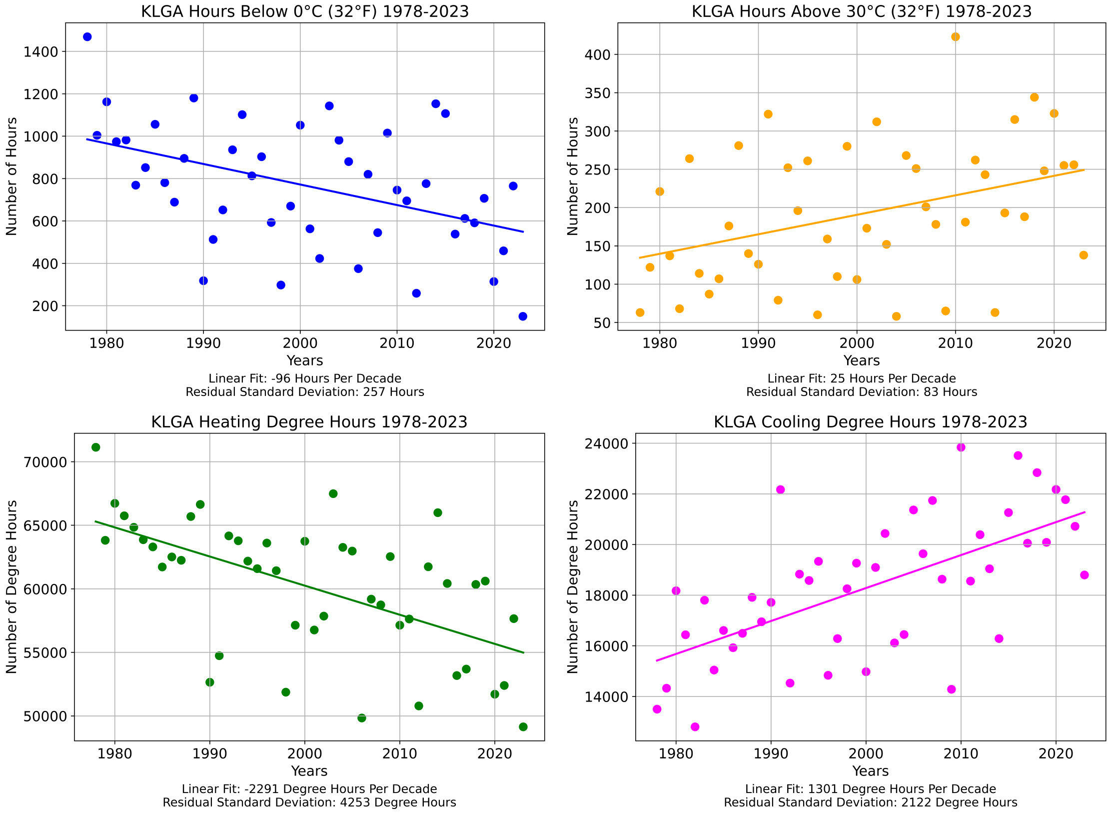

Fig 3. (top left) The number of observations below 0°C (32°F) and (top right) above 30°C (86°F), along with (bottom left) the counts of heating degree hours and (bottom right) cooling degree hours, for LaGuardia Airport (KLGA), New York from 1978 to 2023. A linear regression model is used to depict the overall long-term changes for each metric. For KLGA, the linear fit equates to a loss of about 18.5 days (446 hours) worth of below freezing temperatures and gain of about 5 days worth of temperatures above 30°C (86°F) between 1978 and 2023. The residual standard deviation describes the year to year variability of each metric.

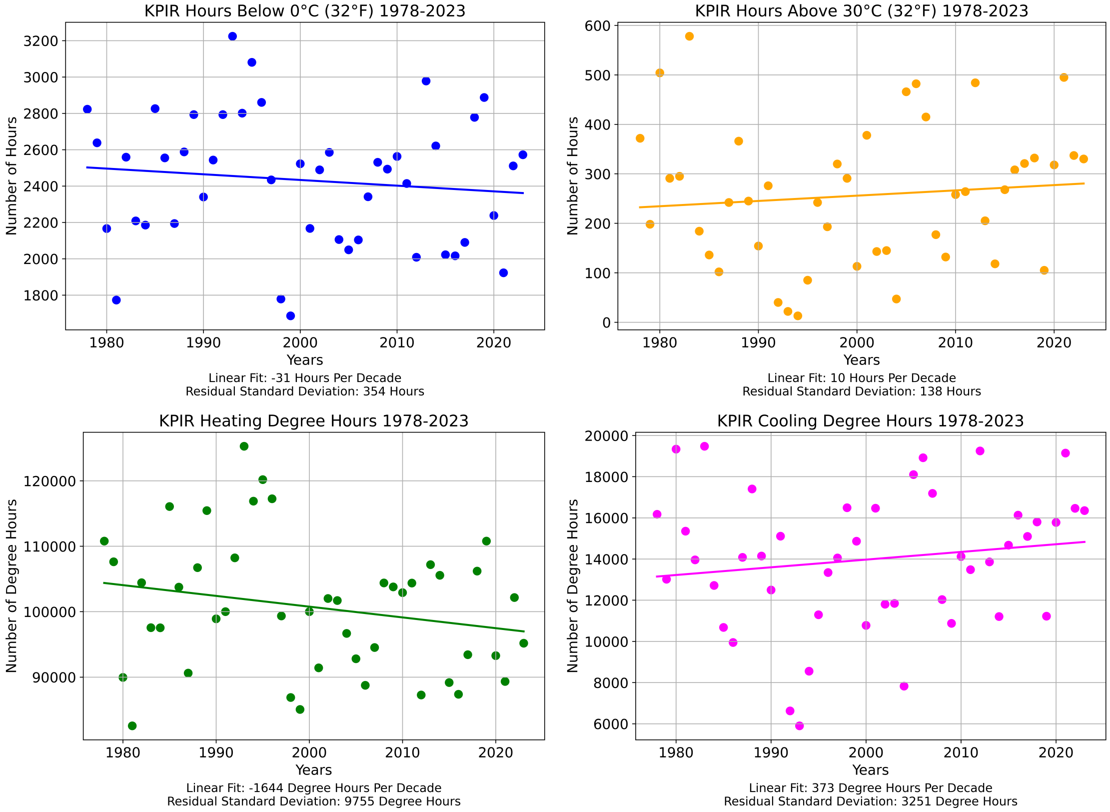

Fig 4. (top left) The number of observations below 0°C (32°F) and (top right) above 30°C (86°F), along with (bottom left) the counts of heating degree hours and (bottom right) cooling degree hours, for Pierre Regional Airport (KPIR), South Dakota from 1978 to 2023. A linear regression model is used to depict the overall long-term changes for each metric. The residual standard deviation describes the year to year variability of each metric. Despite demonstrating non-zero trend magnitudes particularly in the winter season, these trends are insignificant due to the overall high variability.

46 observations in each station sample, the .05 threshold would be classified as a fair significance for this sample size [34]. By this criteria, the metrics illustrated for LaGuardia Airport (KLGA) in Figure 3 are all statistically significant trends. In comparison, the trends for Pierre (KPIR) in South Dakota (e.g. 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 [31, 32]. 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 [30, 31]. Furthermore, permutation tests have the ability to yield powerful statistical results for small sample sizes which applies to the 46-year time range analyzed [30, 33]. 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 [35–38], the permutation test adequately serves the purpose of testing the significance of the simplified linear regression trend.

Information on year-to-year variability is extremely relevant for climate change adaptation as more variable historical conditions make it more difficult to anticipate near future conditions. We can obtain information on the nature of variability for each station by examining the relationship between trend magnitudes and residual standard deviation (Fig. 5).

Smaller residual standard deviations imply better linear trend fits as compared to higher residual standard deviations. 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 (orange dots in Fig. 5). 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. 5). 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 (black dots in Fig. 5). For each of the four metrics in Fig. 5), 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 upon 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. 6) and 7).

Factors that influence short-term local and regional climate patterns include atmospheric-ocean coupling phenomena such as the El Niño/Southern Oscillation and the North Atlantic Oscillation, solar activity cycles, volcanism, and other types of atmospheric and oceanic variability [35, 37, 38]. Anthropogenic climate change and land-use and surface cover changes, including urban heat island and ecosystem changes, 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.

Results

Threshold Temperature Trends and Variability

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 aimed at policymakers [3]. Analyses of the 46-year period from 1978 and 2023 are relevant for planning for anticipated changes in next 10-20 year time frame [39].

In the winter season, large negative trends in hours below 0°C (32°F) are clustered in the northeastern portion CONUS (Fig. 6). For locations in east of the Mississippi River and north of 37° latitude, these trends correspond with a decrease of about one and a half to two weeks worth of hours below freezing since the early 1980s. West of ∼93°W, most locations in Minnesota, Iowa, North Dakota, South Dakota, Montana, Wyoming, and Washington and the 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 in the southern US states as compared to more northern locations since there are fewer hours $\leq$ 0°C (32°F) in southern locations overall.

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. 6). 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 about 1.5 weeks worth of hours since the late 1970s. Many stations in the central US (Nebraska, Kansas, Missouri, Illinois, Indiana, Oklahoma, and Arkansas) indicate high variability and no significant trends in hours $\geq$30°C.

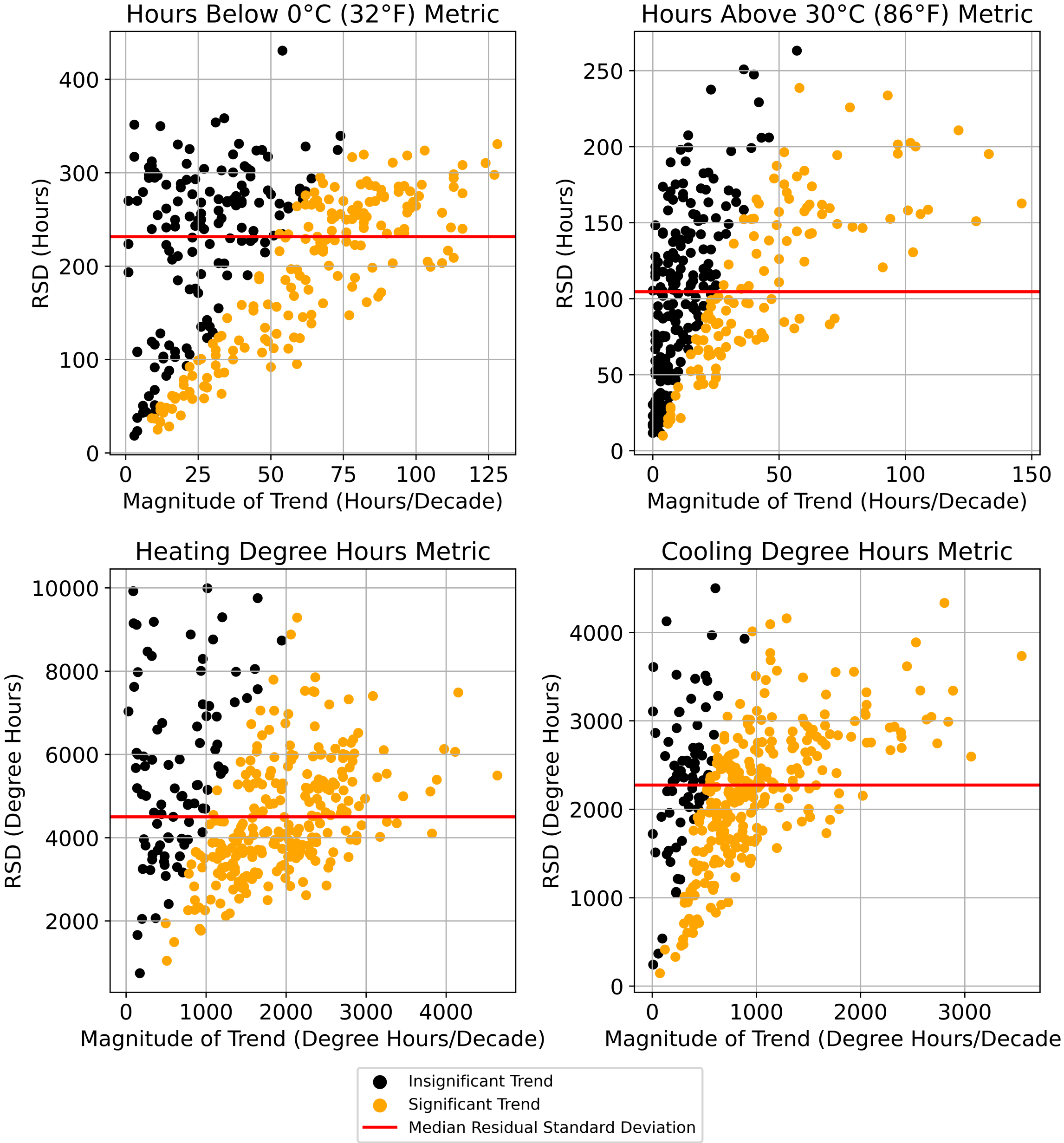

Fig 5. Trend magnitude and residual standard deviation for stations with significant trends (orange dots) and with insignificant trends (black dots) as determined by the permutation test. Median residual standard deviation shown by red line in each panel. (top left) Hours below freezing, (top right) Hours above 30°C, (bottom left) Heating degree hours, (bottom right) Cooling degree hours.

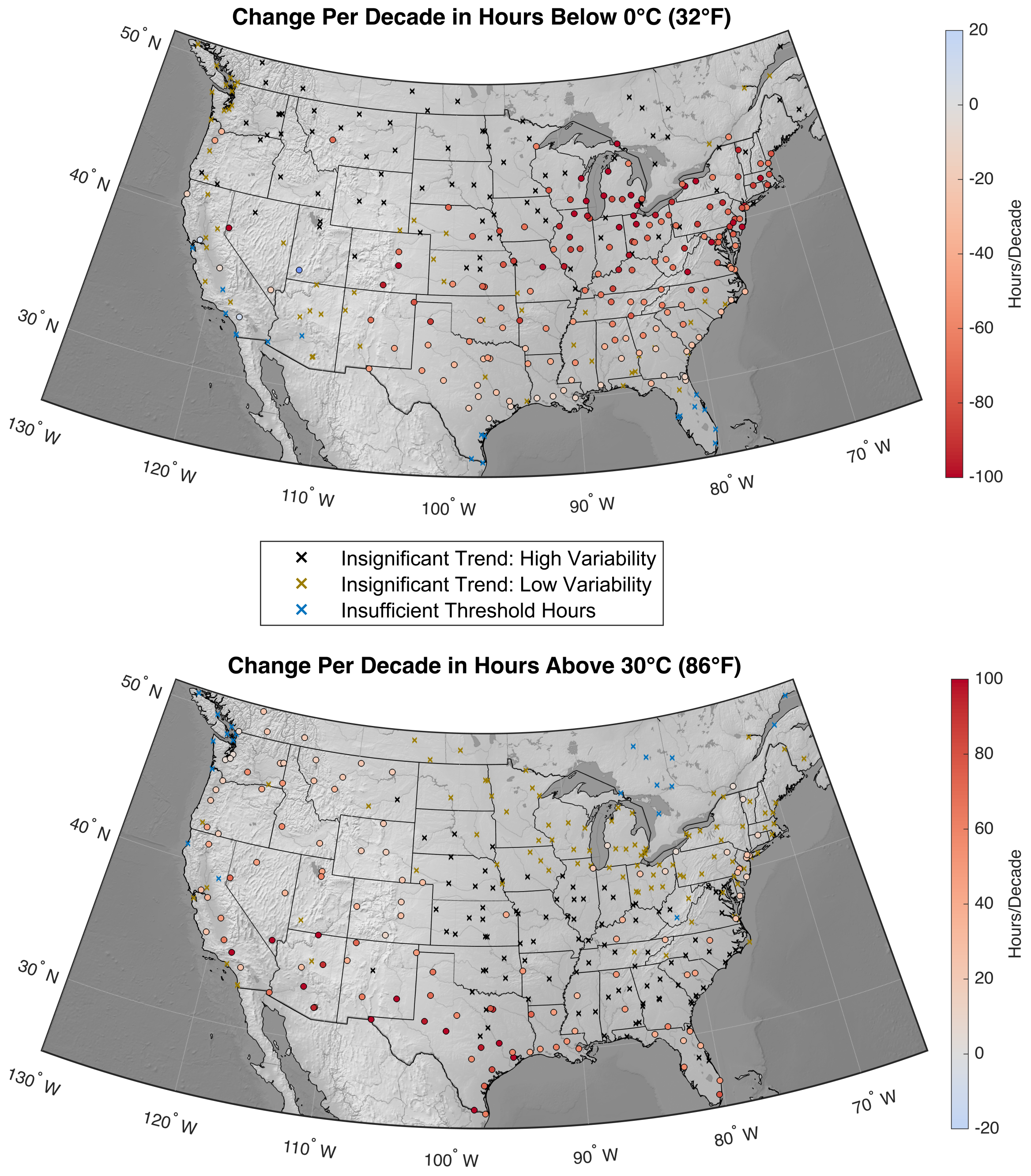

Fig 6. Changes in (top) the number of hours below 0°C (32°F) and (bottom) number of hours above 30°C (86°F) from 1978-2023 for 341 airports across CONUS and southern Canada. Statistically significant trends in units of hours per decade (colored circles). Trends representing warming are denoted in shades of red and orange for both maps. Stations without significant trends are divided into categories of high variability (residual standard deviation $\geq$ 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 less than 10 threshold hours each year for the corresponding metric across the 46 year period.

Heating Degree Hours and Cooling Degree Hours

The regional analyses of both degree hour variables (Fig. 7) complement the findings illustrated in the air temperature threshold maps (Fig. 6). 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 the states of Florida and Louisiana, southeastern Texas, and portions of the southwest. In summer, locations near the geographic center of CONUS (esp. Oklahoma, Kansas, Nebraska, South Dakota) often have high variability in cooling degree hours without significant trends.

Winter warming often offsets summer warming in terms of the degree hour energy use proxy (Fig. 8). The 185 stations that have both significant heating and cooling degree hour trends are divided into four quadrants using their position relative to 37° latitude and -98° longitude. For all stations in the Northwest and most in the Northeast, the reduction in heating degree hours in winter is outpacing the the increase in cooling degree hours in summer (Fig. 8). This also holds true for approximately half of all stations in the southern half of CONUS. In winter, locations with high variability in heating degree hours without significant trends occur in southern Canada, Montana, Wyoming, and the Dakotas and in high-altitude locations in western states.

Conclusions

Analysis of CONUS and southern Canada historical hourly weather station observations from 1978 to 2023 reveals the variability and trends of the impacts of recent climate changes. Hourly data provides a higher degree of granularity that can support analyses of temporal and diurnal variations that daily data cannot provide. We examine several societal relevant metrics based on hourly temperature data: hours below 0°C, hours above 30°C, heating degree hours, and cooling degree hours. We calculate trends based on linear regression and assess their significance based on a permutation test. Where decadal statistics show spatially consistent values among nearby stations, it increases confidence in the findings. It is simpler to plan and to justify adaptation strategies for locations with clear trends. Stations with low variability and without significant trends experienced small changes in recent decades. Stations with high variability and without significant trends are challenging from adaptation standpoint as it is difficult to anticipate likely near future changes.

This detailed hourly analysis complements previous work based on the daily temperature record [1–3]. The key findings of this analysis are:

- Many stations in southern Canada and the north central US (North Dakota, South Dakota, Minnesota, Wisconsin, Iowa, and Nebraska) lack clear decadal trends in hours $\leq$0°C and $\geq$30°C.
- Most stations east of the Mississippi River ($\sim$92°W) and north of $\sim$37°N latitude have lost the equivalent of $\sim$1.5 to 2 weeks or more of temperatures lower than freezing. These locations also typically have smaller magnitude trends of warming in summer than in winter.
- Many stations in Arizona, New Mexico, and parts of southern Nevada, southern California, and southern Texas have gained the equivalent of $\sim$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 Northeast and Northwest portions of the US have lost more heating degree hours than gained cooling degree hours which suggests a net decrease in annual energy use based on this proxy.

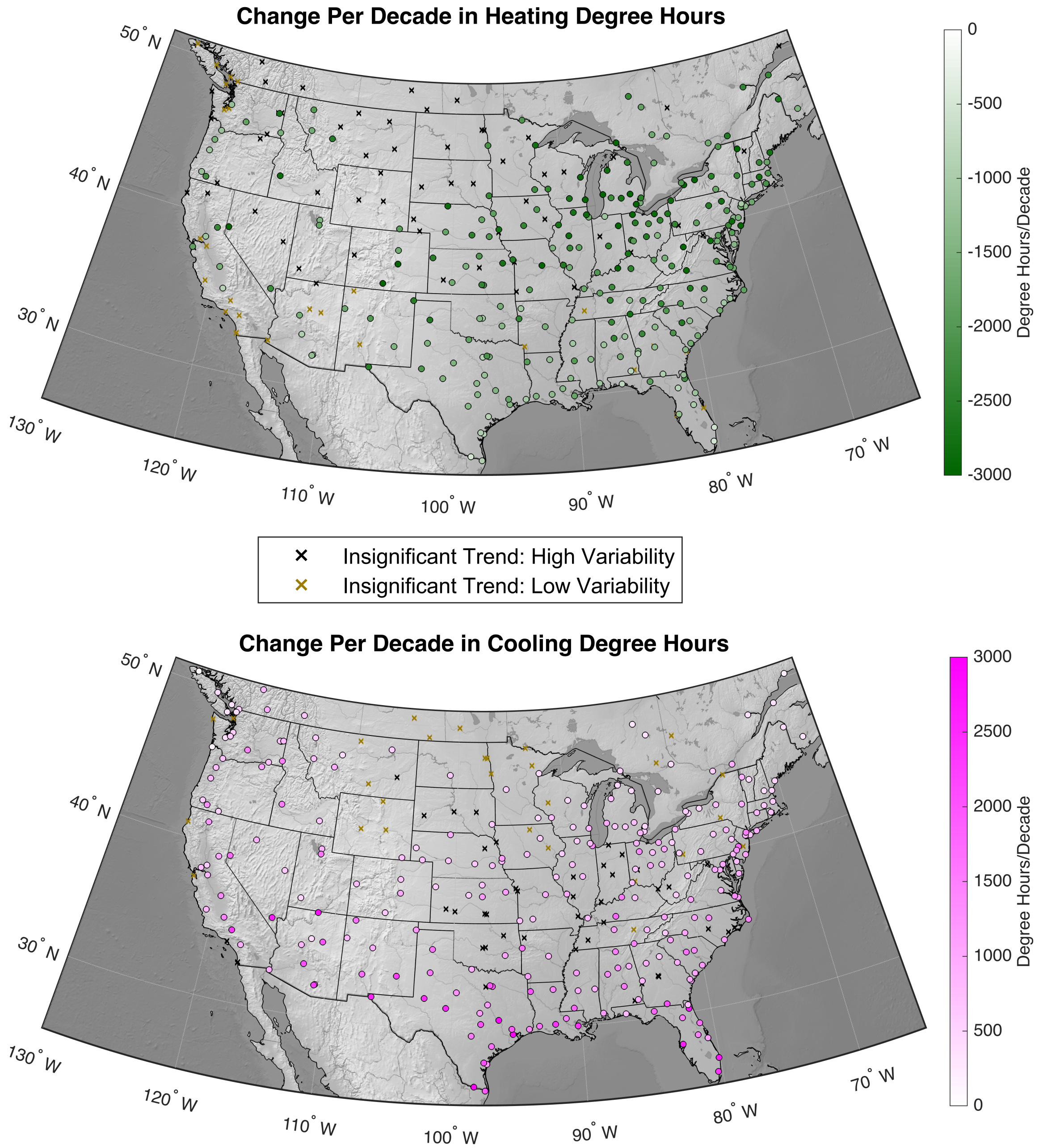

Fig 7. The long term changes in (top) the number of heating degree hours and (bottom) cooling degree hours from 1978-2023 for 340 airports across CONUS and southern Canada. Statistically significant regression trends are colored by magnitude in terms of degree hours per decade. Stations without significant trends are divided into categories of high variability (residual standard deviation $\geq$ median residual standard deviation) or low variability (residual standard deviation $<$ median residual standard deviation).

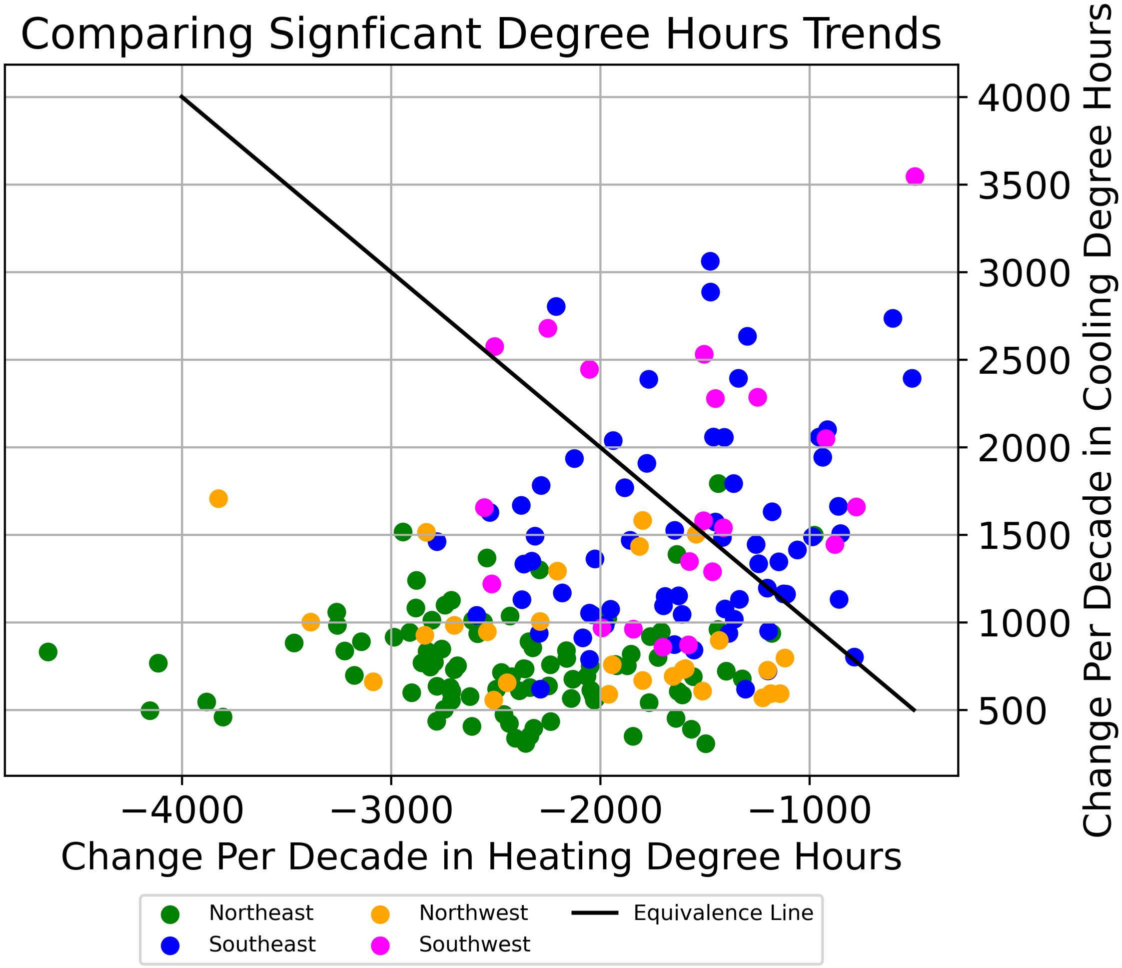

Fig 8. Trends in heating degree hours compared to trends in cooling degree hours for subset of 213 stations that have both significant heating degree hours and cooling degree hours trends. This subset of stations is further divided into geographic quadrants separated by 37 deg N latitude and the 98 deg W longitude 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 half of both southern regions (cyan and pink), the reduction in energy usage (heating degree hours) in the winter is outpacing the increase in energy usage (cooling degree hours) in the summer.

Examination of hourly air temperature data is potentially useful for other societal relevant climate impacts such as 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 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 [40]. The degree to which insect populations survive the winter is related to both snow pack and temperature changes [41]. The increased length of the growing season by 10 to 20 days in many regions of 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 [42].

The urban heat island effect has been shown to locally increase temperatures in and near cities increasing the risks of heat stress and heat related illnesses for those living in urban areas [43, 44]. For example, [45] 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 higher during the winter. 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 [46]. 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 [47].

Hourly energy use proxies can illuminate and quantify energy usage variability at a finer time scale compared to daily or seasonal proxies that either do not capture or underestimate these features [24, 25]. High year to year variability brings the potential for reserve energy margins to be frequently stretched beyond the anticipated average seasonal peak capacity during long periods of exceptionally high or cold temperatures.

Communicating trends as well as variability is crucial for aiding the public's understanding of climate [48]. A given winter may not always be warmer than the one preceding it. Effective scientific communication strategies can further engage the public with these issues [21, 22]. How the human mind processes the temporal aspects of a changing climate differs for shorter versus longer periods of time [49]. Data story telling, and methods that connect with audience personal experiences can help to reframe issues to make them more relevant and actionable [50].

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 equivalent of a lost 1.5 weeks of temperatures below freezing for the northeast US makes makes it more tangible than reporting that average winter season temperatures have increased by 2°F. Communication of impacts based on hourly data analysis helps to connect lived experience to quantitative values that can be used by policy makers, businesses, and homeowners to justify and to plan climate adaptations such as targeted modifications to infrastructure. We believe that these types of analyzes could serve as part of a science communication strategy to engage the public and decision makers and to motivate pragmatic climate action.

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