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Temperature Trends in the Northeastern United States from 1950-2018

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Introduction:

Over the last decade, there has been an ever-increasing interest in global anthropogenic climatic change and its impacts on the environment and societies across the world. This has been fueled largely by public interest and media coverage of reports made by the International Panel on Climate Change (IPCC) implying that, “Limiting global warming to 1.5 °C would require… unprecedented changes” (IPCC 2018). The IPCC report goes further, listing consequences of exceeding this threshold, including impacts on sea level, tropical storms, droughts, and biological systems to name a few. Many predictions are dire, for example, “Coral reefs would decline by 70-90 percent with global warming of 1.5 °C” (IPCC 2018). The IPCC report released in 2022 also contains very similar consequences, stating that the impacts of climate change, “have reduced food and water security… extreme heat events have resulted in human mortality and morbidity” (IPCC 2022). The scientific consensus is that CO_2 emissions are increasing and this is the primary driver of current climate change. The general hypothesis is that temperatures are trending upwards at an alarming rate is a very important aspect of terrestrial and aquatic ecosystem research. Significant changes in temperature can have massive impacts on all organisms across all food webs.

While the IPCC is the main producer of such news, there are many scientists that are in agreement that climate change is an existential threat to humanity. For example, there is much research surrounding the impacts of anthropogenic climate change on extreme weather patterns. One such study, looking at the results of climate models, purported findings showing an, “increase in interannual variability of the Indian monsoon [season]” (Easterling et. al. 2000). Within the United States, this same study noted the increasing cost of storms, “$100 million annually in the 1950s to $6 billion per year in the 1990s”, also noting that the number of catastrophic storms has increased in this same time frame. This is a very concerning statistic, that the United States alone is spending sixty times more on catastrophic event remediation than it once was.

There are also numerous studies implying that climate change, and specifically climate warming, is causing declines of some species to the point of extinction, and at the same time increases in others. For example, one study looking at species dynamics within tick populations found an increase in ticks that carry diseases that impact humans (Gatewood et. al. 2009). The argument being that these disease bearing ticks survive better in milder climates, and when temperatures get warmer ticks are able to spread to once colder areas that they could not have survived in prior to climate change. The Gatewood et al. (2009) study, and since that time other reports (Beard et. al. 2016), warn of this trend, that if temperatures keep going up, we will see an increase in the spread of Lyme Disease into new areas. Further, mosquitos are another common insect that is said to expand its range with climate change, and therefore will result in an increase in malaria (ha et al. 2014), West Nile virus (Paz 2015) Dengue (Tran et al. 2020), and other insect-carrying diseases. A study by Epstein et al. (1998) was one of the earliest reports to suggest that mosquitos could serve as bioindicators for climate change trends, asserting that, "provided sufficient moisture, warmer temperatures – within the survival ranges – increase mosquito populations, biting rates (blood meals), mosquito activity and abundance." As a result, the spread of mosquitos is considered by the media as a threat to global human health.

Based on recent trends and media coverage, it is not shocking or even surprising to witness the responses of politicians, citizens, and policy makers based on model projections. In November 2021, the Biden Administration authorized $50 billion in funding for climate change catastrophes. It is not just the United States taking action, many countries and companies are pledging “net zero” CO_2 emissions. Governments are responding to their citizens’ who are, in turn, responding to the media-driven belief that climate change will have dire consequences on human populations.

On many regional or local levels, there are reports summarizing the potential impacts of climate change. Many state agencies have released information on the projected impacts of climate change on their specific states (Reidmiller et al. 2018). For example, in Connecticut a report compiled in 2011 by the town of Groton lists a number of local impacts. First, the report finds that since 1970, annual average temperatures have increased 2˚F (1.1˚C). The paper discusses sea level rise as well, stating that the town of Groton, CT will be “underwater” in the near future. This study further projects an increase in vector-borne diseases such as West Nile Virus and Lyme Disease, droughts, heavy precipitation and a decrease in snow.

A trend that seems to be developing, especially at regional and local levels and often driven by what can be viewed as unbalanced media coverage, is that practically every environmental issue being reported is linked primarily, if not exclusively, to climate change. The fact that other contributing variables are often down played or even overlooked in response to potential impacts of climate change can have significant consequences on how environmental issues are addressed on regional and local problems The Epstein et al. (1998) and Gatewood et al. (2009) studies looking at mosquito and tick populations, respectively, do not address other variables such as predator-prey dynamics and carrying capacities of ecosystems. Both studies purport that given an increase in air temperatures, the populations of these insects will thrive. There is no mention of an increase in predators that could also occur, limiting population growth. There is also no mention of the carrying capacity of the ecosystems they spread into, meaning these ecosystems may not have the necessary resources to support rampant growth of these organisms. This, however, is not the case. In contrast, the importance of variables in addition to temperature is exampled by Abrams and Nowacki (2018) who concluded that, “fire and vegetation changes were likely driven by shifts in human population and land use beyond those expected from climate alone.” Unlike the Abrams and Nowacki (2018) investigation, many studies are focused on climate, and specifically temperature, rather than other variables that are just as important.

It is well established that bird populations are declining in North America (Rosenberg et al. 2019). Habitat loss associated with land use change is often reported as the primary contributing factor to the decline in bird populations (Pennisi, 2019; Craig et al., 2022). However, in reporting results from such studies, although subtle, climate change and not habitat loss is often emphasized. For example, although Craig et al. (2022) show the major impacts of habitat loss, they stated, “Expected effects of climate change on populations were consistent with some findings, but habitat effects appeared related to a greater number of shifts.” Similarly, Pennisi (2019) commented, “Climate change, habitat loss, shifts in food webs, and even cats may all be adding to the problem, and not just for birds.” Even in a local newspaper story (Silber, 2022) discussing the findings of the Rosenberg et al., (2019) study, scientist Brooke Bateman states, “Birds Are Telling Us It’s Time to Act on Climate Change.” This is not to suggest that climate change is not important, but rather that without addressing habitat loss, the crisis with birds will not improve.

Examples of factors being more important than climate change with respect to local issues can also be observed in aquatic ecosystems. For example, without any direct evidence, local and state agencies assumed cyanobacterial blooms in Candlewood Lake, CT, were caused by climate warming. However, using a 35-year database, Siver et. al (2018) found that, “despite the lack of trends in air temperature", they observed a, "decline in the temperature of the hypolimnion [yielding] an increase in thermocline strength." This study found that wind speed was highly correlated with in-lake dynamics and that air temperature was not important. In fact, based on local air temperature records, there has not been a significant increase since 1985. In another local example recently published in the Rivereast News Bulletin (January 21, 2022), it was suggested that a winter fish kill in Lake Pocotopaug, CT was caused by the impact of climate change on water temperatures and ultimately growth of algae. However, this waterbody has a long history of eutrophication issues and previous fish die-offs. The article does not cite any air or water temperature data.

It is important to analyze temperature trends in a given region with respect to an environmental issue, and not make the assumption that warming has occurred. This is especially important when evaluating changes in freshwater resources on a local or regional scale, and not to use generalizations for larger and more expansive areas. The objectives of this study are to a) develop long term temperature datasets for specific localities in the northeastern United States that can be used in conjunction with existing datasets to aid in understanding shifts in freshwater lakes; b) analyze each individual site for trends in temperature for all seasons over a 69-year period and; c) examine temperature trends, if any, for the region based on combined dataset of all sites.

Methods:

The northeastern states included in this study are: Connecticut, Massachusetts, Maine, New York, Vermont, New Hampshire, and Rhode Island. Thirteen sites were selected to represent a range of geographic and land use throughout the northeastern United States. The data for each site were derived from weather stations operated at established airports. Airports maintain weather stations and many have operated continuously since 1950, yielding one of the most reliable collection methodologies of long-term records.

The data for each airport was assembled from databases maintained by Weather Underground (www.wunderground.com). Weather Underground databases hold historical temperature readings for all sites, with records dating back to at least 1950, and in some instances back to the 1930s. For this study, data was collected for the period 1950-2018. This 69-year time span was available for each site, resulting in an almost complete dataset for the suite of sites.

The historical Weather Underground database contains mean minimum, mean average and mean maximum temperatures for all months. For this study, data was used for the months of January, April, July, and October, to represent each of the four seasons. All data were downloaded, stored in excel files, and used to build tables for each site, and used for all analyses.

Linear regressions, polynomial regressions, and an Autoregressive Integrated Moving Average (ARIMA) were conducted to determine long term trends in temperature. Standard error statistics were generated and plotted for all datasets to estimate variability within various subsets of the data, for example, standard error statistics were plotted for all sites that are non-ocean front vs sites that are near the ocean. Standard error statistics were used rather than standard deviation since all data points analyzed represented averages of daily temperature readings for given months. Standard error is the typical way to measure deviations among sample(s) of means. Standard error statistics were plotted using Excel to analyze for potential trends in that statistic. Scripts were written in Python to automatically analyze multiple datasets at once, particularly for packages such as Pandas (www.pandas.pydata.org), Numpy (www.numpy.org), and StatsModels (www.statsmodels.org/stable/index.html#) used for various data cleaning and analysis capabilities.

Prior to running the time series analyses, basic graphical and statistical exploration was conducted. For each site, graphs for all four months were produced for mean minimum, mean average and mean maximum temperatures (ºC, y-axis) versus time (years, x axis). Graphs for each month containing mean maximum, mean average and mean minimum readings were developed for the 68-year period across all sites. The standard error was calculated for each variable and distribution graphs were made to determine the variation in temperature for each site/month. Means and number of days in each month over or under the lower and upper inter quartile ranges (IQRs) were also calculated. These same statistics were calculated for the average temperature across all sites for each month, and for the average of all sites and all months to estimate the annual temperatures for the entire region. These analyses were done in Microsoft Excel.

Secondly, Geographic Information System (GIS) was utilized to investigate the geospatial aspect of the temperature data. The mean temperature for each site and month was mapped using an overlay on a template map from the software QGIS (Quantum GIS) and our mean average temperatures and site coordinates from a csv file. The geographic variables distance from the ocean, distances between sites, elevation, aspect, and population size, were taken into account when analyzing potential temperature trends across the region.

The statistical techniques, linear regression, polynomial regression, and autoregressive integrated moving average (ARIMA), were conducted to evaluate magnitude and significance of temperature trends observed during 1958 to 2018 at 13 sites. A simple linear regression model is used to study whether there is any significant trend in temperature (dependent variable) over time (independent variable). Several metrics, the coefficient of determination (R^2), magnitude and direction of the regression coefficient (beta-hat), and overall significance of the regression (p-value), were used to evaluate the performance of the linear models. R^2 represents the amount of variability in the response variable (temperatures) that is explained by the model (time), where the higher the R^2 value the greater the explanatory ability of the model. Some models can have low R^2 values and still be deemed significant, which is the why p-values were also analyzed for each linear regression model. If a model had a low R^2 value and the coefficient was not significant, it was concluded that the linear regression model could not explain any relationship between year and temperature.

Polynomial regression models are used to track non-linear relationship between variables of interest. Similar to the linear regression models, the polynomial regression analysis was used to test for significant linear or non-linear trends between temperatures (response) and time (independent). A key parameter in a polynomial regression model is the order of the polynomial. For example, a first-order model is the same as the linear regression, a second order polynomial involves two predictor terms, years and years squared, and so on. Including predictor terms of higher order, that is, increasing the order of a polynomial regression model increases its flexibility and the ability to fit. Or, in other words, by increasing the order you increase the polynomial regression's ability to explain non-linear relationships. To test the fit of the polynomial regression, the same statistics were used as those for linear regression. For polynomial regression models, the p-value is more important in determining significance than R^2 valves. Thus, the p-value was used to determine whether a polynomial regression model is a better fit than a linear regression.

While both of these models can be very valuable in determining relationships between variables, they may not be the best methods to use to determine significant trends over time. In both cases, the models determine the relationship between predictors (year) and responses (temperature) under the assumption that values at a given site are independent over the years, which is unlikely to hold true in this study. A time series regression model which accounts for the inherent dependence among observations recorded over time is more accurate. In this work autoregressive integrated moving average (ARIMA) time series models were used. An ARIMA model utilizes past values for the dependent variable to model the current values which are estimated. There are three orders that the model utilizes to create the function for past values to estimate current ones, p (autoregressive model), q (moving average model) and d (discrete value representing seasonality). The value of p, the autoregressive operator, represents the number of years back the model will iterate to predict the current year's temperature, meaning if p = 5, then the model will go back 5 years and use those temperatures to determine the current one. The value of q, the moving average operator, is similar in that it determines how far back the moving average operator will go. If q = 5, the moving average operator will calculate moving averages for every five years. Lastly, the value of d, is a parameter used to determine the number of transformations required to get a stationary model (when mean and variance are constant over time). While stationary models have constant variance overtime, you can also have a model with seasonality, meaning that the mean and variance will fluctuate (not remain constant) across the time series. Seasonality in a time series dataset is a trend in fluctuations in temperature that occur on a regular basis, and are spaced out over time, similar to seasonal trends in temperature. In the winter it is typically colder while the summer is typically warmer, those changes in temperature of the dataset are examples of seasonal trends. Thus, the number of seasonal terms identifies the amount of variation which follow these trends.

Two different approaches were utilized to determine the best ARIMA model for the dataset. First, a genetic algorithm was utilized to determine the ideal parameters. Genetic algorithms have been used in many occasions to optimize model parameters based on fit on test or training sets. In this case, the chromosomes were binary versions of values one through ten. The fitness function ran the model for each chromosome and the chromosome's fitness was based on minimizing what the ARIMA model's (Bayesian Information Criterion) BIC value. After five-hundred generations, or iterations, trying different (p,d,q) sets, the genetic algorithm outputs the ideal order set (p,d,q) which when used as orders for the ARIMA model, produced the lowest BIC. The problem with the genetic algorithm-based approach is the chance of overfitting is essentially 100%, the second approach was to utilize Autocorrelation function (ACF) and Partial Correlation function (PACF) plots to determine whether or not correlations between variables change over time (ACF) and whether there are any lags in these changes (PACF). This second approach was to try values that would not lead to overfitting. The model with these orders combines patterns of exponential and linear trends and allows for flexibility to model non-linear relationships while also not overfitting.

The python package statsmodels was utilized to run the ARIMA model. The statsmodels package has several methods that efficiently run and provides outputs for several different models. In this case, the SARIMAX() method was used, which allows one to input the p, d, and q values as orders for any input dataset. The output of the function contains a wide variety of information, ranging from BIC (Bayesian Information Criterion) to Heteroskedasticity and Skew.

Results:

Site and Data Information:

Thirteen sites were analyzed in this study, from seven northeastern states (site counts are in parenthesizes): Maine (1), New Hampshire (1), Vermont (1), New York (4), Massachusetts (2), Rhode Island (1) and Connecticut (3) (Figure 1). The sites range in latitude from 41.311 to 44.699 and longitude from -70.255 to -78.878 (Table 1). Specifically, the furthest north site was Burlington, VT, the furthest south site was New Haven, CT, while the furthest west site was Buffalo, NY and the furthest east was Portland, ME. The weather stations associated with the sites were all situated at airports, all of which have recorded continuous temperature data over all, or most of the study period.

The main criterion when selecting each site was to make sure they had as consistent data as possible over the study period (1950-2018, 69 total years), and that they contained these data for all four months: January, April, July and October. Some of the data are missing, mostly because of airport renovations. Except for Plattsburgh, NY, all sites had complete or near complete datasets for all four months for the mean average, mean minimum and mean maximum temperature (Table 2).

Out of the possible 3,588 potential observations for mean average temperature, 3,450 were recorded (Table 2), 138 observations are missing, or 4% of the potential total data. Of these missing observations 74 came from Binghamton, NY. The average number of observations for each of the sites is 66, meaning that on average our datasets account for roughly 96% of the study period. In each of the four months, all sites except Ithaca, NY, Danbury, CT, and Binghamton, NY, consistently had observation counts greater than 66. Most of our sites had at least 96% coverage and multiple (5 of the 13) sites had complete datasets for all months.

Other geographic site variables were examined during this study, including altitude of the site and whether the site is situated on or close to the coast. The altitude ranged from 3.7 (New

Haven, CT) to 439.7 (Binghamton, NY) meters above sea level (Table 3). While not the lowest in elevation, Boston, MA is also worth noting as its elevation is only 6 meters. The average altitude for all of the sites was 135.1 meters. The determination was also made whether or not the site represented an ocean front site. To determine this, a buffer of 10 km was defined, meaning that if the site was within 10 km of the ocean, it is considered to be an ocean front site. Of the 13 sites in this study, 4 were within 10 km of the ocean: Boston, MA, New Haven, CT, Portsmouth, NH, and Portland, ME (Table 4). The majority of sites did not meet this threshold, (9/13 or 69% are outside the 10 km buffer). In general, the ocean sites represent the lowest elevations.

Descriptive Statistics:

Basic descriptive statistics were collected for all datasets, including the mean, range and standard error of each of the temperature metrics (mean maximum, mean average and mean minimum) for each of the sites and months (Table 5). The average of the mean temperature for the month of January was -4.1°C, and no site had a mean minimum or mean average that exceeded 0°C. However, most mean maximum values were greater than 0°C (except for three sites) (Table 5). The mean minimum ranged from -5°C (Boston, MA) to -15.7°C (Binghamton, NY) (Table 5). The mean average temperature ranged from -0.5°C (New Haven) to -7.6°C (Plattsburgh, NY). The mean maximum temperature ranged 9°C (the largest range for the mean maximum metric), from 8.3°C for Warwick, RI to -0.7°C for Ithaca, NY (Table 5).

For the month of April, the average of mean average temperatures across all sites was 7.9°C (Table 5). The overall mean maximum metric (6.1°C) was smallest during the month of April (Table 5). The warmest site with respect to the mean average temperature during April was New Haven, CT (9.9°C), while the coldest was Plattsburgh, NY (6°C) (Table 5). The range for the mean minimum temperature during April was 5°C for Boston, MA to -2.2°C for Binghamton, NY (-2.2°C) (Table 5). The range for the mean maximum was from Portland, ME (11.4°C) to the warmest site being Binghamton, NY (17.5°C) (Table 5).

During the month of July, the average mean temperature was 22.1°C (Table 5). The range for the mean average metric for July was largest during the month of July (8.1°C), this range was from New Haven, CT (27.9°C) to Binghamton, NY (19.8°C) (Table). The only site to have a mean average fall below 20°C was Binghamton, NY. The range for the mean minimum temperatures was from Boston, MA (18.9°C) to the coldest site being Binghamton, NY (13.9°C) (Table 5). The range for the mean maximum was also the lowest for this metric, with a range of 4.7°C, from the warmest site, New Haven, CT (29.8°C) to Binghamton, NY as the coldest site (25.1°C) (Table 5).

For the month of October, the average mean temperature was 10.6°C (Table 5). The range for the mean minimum metric was from Boston, MA (8.7°C) to the coldest site being Binghamton, NY (1.3°C) (Table 5). For the range of the mean average metric, the warmest site was New Haven, CT (13.2°C) and the coldest site was Plattsburgh, NY (8.5°C) the range of this metric was 4.7°C. The range for the mean maximum metric from 6.2°C with the warmest site being New Haven, CT (20.1°C) to the coldest site being Burlington, VT (13.9°C) (Table 5).

The relationship between temperature and site latitude for each month is displayed in Figures 2-5. The linear regression model and R^2 value is given for each relationship. As is apparent, more southern sites generally have warmer temperatures, across all months. The relationship is not as pronounced however in July where the linear regression model has a R^2 value of 0.35 (Figure 4), while the R^2 values were greater than 0.5 for the other months (Figures 2, 3 and 5). The weaker relationship in July is caused by the New Haven, CT site, which has a significantly higher mean temperature than all other sites (27.9°C) (Table 5, Figure 4). The low R^2 value could also be due to July having the largest mean temperature range out of all the months (Table 5).

As noted, ocean front sites (Boston, MA, New Haven, CT, Portsmouth, NH and Portland, ME) were defined as being within 10 km of the ocean. When these sites are removed from the scatter plots, the relationships between latitude and temperature for all months becomes even stronger. Besides July, the R^2 value of the linear regression line improves when ocean-front sites are removed. The R^2 for the July model decreases when the ocean-front sites are removed, even if only New Haven, CT is removed (Figure 8). The impact of latitude on temperature is most apparent during the month of April with a R^2 value of 0.71 without ocean-front sites (Figure 7) and 0.69 when including the ocean-front sites (Figure 3).

Variability Analysis:

In addition to descriptive statistical analyses, various metrics relating to variability were analyzed. Initially, variability in annual temperature was measured using standard error for each site-month combination. Based on this metric, colder months, especially January, had significantly higher variability (higher standard errors scores) than warmer months. This was true for all three-temperature metrics, mean minimum, mean average and mean maximum across sites (Figures 9-11). For all sites, the month of January had the highest standard error with respect to the mean and mean minimum temperature, while the month of July had the lowest standard error (Figures 9-11). However, the mean maximum temperature slightly deviates from this trend, where Plattsburgh, NY and New Haven, CT had higher standard errors for the month of April rather than January (Figure 11). That being said, July still had the lowest standard error for the mean maximum metric for both of these sites (Figure 11).

While the trend does not exist for all months, standard error is correlated with latitude, where the southernmost sites have slightly less variability than the northern most sites (Figure 12). In order to further explore relationships in temperature variability, coastal sites were removed from the analysis because ocean sites are known to have less variability relative to more inland sites. After removal of the ocean-front sites (Boston, MA, Portsmouth, NH, Portland, ME and New Haven, CT) the relationship was much improved with an increase in R^2 from 0.38 (Figure 12) to 0.59 (Figure 13), this measure gleaned a potential relationship between latitude and temperature variability. Temperature variability was also examined using box and whisker analyses by month. This analysis confirmed that the month of January had the highest variation in temperature, while July has the least variation (Figure 14). Temperature variations for the month of January were also greater on a year-to-year basis, that is, experienced greater swings between years. Line graphs were constructed by subtracting the prior year's temperature from the current year (e.g., 1969's temperature from 1970's temperature). These data were plotted over time for the months of July and January, the months with the extremes in temperature variability (January being the most variable, July being the least variable). These results further confirm that there was significantly more year-to-year variability in January than in July (Figures 15-16).

Regression and Time Series Analysis:

Three types of regressions were run against the time series data: linear regression, polynomial regression and an ARIMA model. All models were run on the mean average temperature data metric for all sites and months (Figures 17-20). Linear models were visually analyzed and tested for significance, and polynomial and ARIMA models were analyzed to examine trends. The R^2 value and the p-value of the coefficient were used to measure how well the linear regressions fit the data, with year being the predictor. In the case of the linear regression, there is one predictor, which is the year. The p-values listed in Tables 6-9 represent the significance (if $p<0.05$) of the linear relationship between temperature and year.

For the month of January, the average R^2 for the linear regressions across all sites was 0.017, meaning that on average, the linear regressions explain 1.7% of the variation in January temperature. All of the R^2 values were less than 0.15, with the largest being 0.102 (Plattsburgh, NY) and the smallest being 0.0001 (Portsmouth, NH) (Table 6). Given these low R^2 values, there were also no significant coefficients for any of the linear regressions. For the month of April, the average R^2 across all of the linear regressions for all sites was 0.036. Similar to January, no R^2 exceeded 0.15 for the month of April, with the largest being 0.107 (Portland, NH) and the lowest being 0.0001 (Danbury, CT and Ithaca, NY) (Table 7). While there were no adequate R^2 values, two regressions had slightly significant year coefficients (Burlington, VT and Portland, ME) (Table 7). The month of July also yielded linear regressions with low R^2 values, with an average R^2 value across all sites of 0.056. None of the linear regressions for July had a R^2 value greater than 0.18, with the lowest being 0.0001 (New Haven, CT) and the largest being 0.171 (Burlington, VT) (Table 8). While there were no large R^2 values, four of the linear regressions had significant coefficients (Burlington, VT, Windsor Locks, CT, Portland, ME, Worcester, MA) (Table 8). The month of October had the lowest performing linear regressions when comparing R^2 values, with an average across sites of 0.014. None of the linear regressions had R^2 values greater than 0.06, the largest was 0.056 (Portland, ME) and the smallest R^2 value was 0.0001

(Buffalo, NY) (Table 9). While the linear regressions in October were the worst performing, one linear regression had a significant coefficient, Portland, ME (Table 9).

After linear regressions were run, polynomial regressions were performed on the same datasets. Even though the R^2 metric is similar for polynomial and linear regressions, the testing metrics differ. Because 6^{th} order polynomials were utilized, there are now six potentially significant coefficients. To measure the fit of the polynomial models, significant coefficients were counted, with a maximum of six significant coefficients (technically, 6^{th} order polynomials can have seven, if the y-intercept is included, however in this case, it was not included).

For the polynomial regressions, the first month tested was January. The average R^2 of polynomial regressions run on the month of January was 0.049. No R^2 values were greater than 0.15, with the maximum R^2 being 0.103 (Plattsburgh, NY) and the minimum being 0.005 (Danbury, CT and Ithaca, NY) (Table 10). Of all of the polynomials run on January, only one had any significant coefficients (Portland, ME: 6 significant coefficients) (Table 10). The polynomial regressions for April had an average R^2 value of 0.083. Similar to January, no R^2 value exceeded 0.15 for the month of April, with the largest R^2 value being 0.131 (Portland, ME) and the lowest was 0.001 (Danbury, CT) (Table 11). One of the polynomial regressions had 6 significant coefficients (Warwick, RI), none of the other regressions had any significant coefficients) (Table 11). For the month of July, the average R^2 value was 0.122, the maximum R^2 value was 0.28 (Warwick, RI) and the minimum R^2 value for the month of July was 0.029 (Ithaca, NY) (Table 12). Four of the polynomial regressions had significant coefficients (number of significant coefficients in parenthesizes): Binghamton, NY (5), New Haven, CT (6), Warwick, RI (6) and Worcester, MA (6) (Table 12). The month of October had the best performing polynomial regressions when looking at both R^2 values and number of significant coefficients.

The average R^2 value for all polynomial regressions during the month of October was 0.118, the maximum was 0.279 (Warwick, RI), and the lowest was 0.049 (Ithaca, NY) (Table 13). The month of October had the most polynomial regressions with 6 significant coefficients, with all but two of the polynomial regressions containing 6 significant coefficients (Danbury, CT and Ithaca, NY both had 0 significant coefficients).

ARIMA models were also run on each site using the mean average temperature of each month. The ARIMA model forms depended on the PACF and ACF plots for each site, only two different ARIMA models were used based on the plots (ARIMA(0,0,0) and ARIMA(0,0,1)). For the month of January, the average BIC was 320.08, with a high of 359.58 (Burlington, VT) and a low of 270.12 (Plattsburgh, NY) (Table 14). For the month of April, the average BIC was 250.49, with a high of 302.35 (Worcester, MA) and a low of 193.29 (Plattsburgh, NY) (Table 15). The month of July had the lowest average BIC of 231.64, and values ranging from 270.94 (New Haven, CT) to 186.31 (Plattsburgh, NY) (Table 16). The average BIC for the month of October was 253.23, with values ranging from a high of 302.81 (Binghamton, NY) to a low of 198.29 (Plattsburgh, NY) (Table 17).

Each of the models (linear regression, polynomial regression and ARIMA) were also run across all sites for each month using the average mean temperature. The results are displayed for the linear (Figures 19-22), polynomial (Figures 23-26) and ARIMA (27-30) analyses. The linear model had low R^2 values, ranging from a high of only 0.023 (April) to a low of 0.001 (October) (Table 18). Only the linear model for July had a significant predictor (Table 18). The polynomial regressions performed slightly better than the linear models with R^2 values ranging from a high of 0.178 (July) to a low of 0.152 (October) (Table 19). However, while the R^2 values were improved, each of the models (except July, which had 2 significant coefficients) only had 1 significant coefficient. The ARIMA model out-performed the other two analyses. The BIC for July (which was the lowest) was 246.06, while the month of January had the highest BIC at (365.38) (Table 20). In relation to the significance of coefficients, the ARIMA run on the temperature for October had 4 significant coefficients and the rest had 1 (Table 20).

While there was little evidence of temperature trends across the entirety of the dataset, a significant cooling period was identified for January from 1950-1970 (Figures 30-32). The same trend was not observed for the other three months. The linear model (Figure 30) polynomial model (Figure 31) and ARIMA model (Figure 32) all performed better on the cooling period than on the entire time period as a whole.

Discussion:

After running linear regressions, polynomial regressions, and ARIMA models on the data, no significant trends in temperature were found for any of the months over the 69-year period for the region as a whole. Given that all three statistical procedures could not identify any trends, up or down, from 1950-2018, it is concluded that there has been no significant increase in temperature throughout the study period for the northeastern United States. This is in stark contrast to the majority of the literature, and many institutions, which all have concluded dangerously significant increases in temperature across the northeastern United States. Our linear regression and polynomial regression models were unable to be deemed statistically significant when using the R^2 values and coefficient p-values as tests. The ARIMA models were able to be deemed somewhat explanatory of the variation observed in our data due to satisfactory BIC values and some significant p-values for coefficients. Even with significance, the ARIMA models did not show any trends in temperature across the entirety of the study period for the region.

Even though no statistically significant trend was observed for the whole time series (1950-2018), a statistically significant decrease in temperature was uncovered for the 20-year period from 1950-1970. This decrease in temperature is most significant for the month of January, and to a lesser degree for the other months examined. Due to this decrease in temperature, there is an observable increase in temperature from 1981 to present. However, without the earlier decrease in temperature, the increasing temperature trend post 1980 does not exist. This finding emphasizes the importance of looking at climate trends over long periods of time rather than finding trends over shorter arbitrary intervals. Given a lack of trends across the entirety of the study period, this data set does not support previous conclusions that significant climate warming has occurred in the northeastern United States since 1950 (Burakowski et. al. 2008).

It is important to note that all three models yielded either insignificant trends or no trend. Polynomial and linear regressions both were unable to define any significant trends up or down in temperature, meaning there were no trends, linear or non-linear, in the temperatures data between 1950 to 2018, which at least refutes a linear increase in temperature over time. These two statistical models proved insignificant based on R^2 values, which represents how much of the variation in the data the model can explain. Because the polynomial regression models had more coefficients than our linear models (polynomials had six variables, linear models had one), R^2 values are expected to increase. As a result, p-values of the coefficients were also used to evaluate the strength of the models. If a polynomial regression model had a relatively high R^2 value compared to a linear regression model, but none of the coefficients were significant, then the model was deemed insignificant. The difference in number of coefficients and model type made it important to employ multiple metrics when comparing models.

Because linear regressions and polynomial regressions attempt to model a relationship between an independent variable and a dependent variable, they present a potential drawback when analyzing time series data. In the case of time series data, this isn't the relationship you are generally looking for, and in the case of temperature trend data, this relationship is typically not going to exist. Linear regressions and polynomial regressions also have slightly different drawbacks as well. Linear regressions are not very flexible, as they only model a linear trend, which rarely exists in the real world, thus making it often hard to apply accurately to real world data. Polynomial regressions do a much better job of modeling non-linear relationships, because their flexibility allows them to be fitted to a non-linear trend. That being said, again, both methods are attempting to define a relationship between an independent and a dependent variable, which for temperature time series data (year vs. temperature) is unlikely to be significant. A relationship is unlikely to exist between temperature and a specific year because a given year itself does not impact temperature. There are several other factors that impact temperature, such as CO_2 emissions, methane emissions, ozone-depleting substances, and increased cloud cover (caused by perfluorocarbons) (Montzka, Dlugokencky, Butler 2011). Due to there being several causes of temperature fluxes, it is highly unlikely for there to be a causal linear relationship between year and temperature (where a specific year is causing a change in temperature).

Given the potential drawbacks of linear and polynomial analyses, ARIMA models were also used to search for trends in our time series data. "Classical regression is often insufficient for explaining all of the… dynamics of a time series" (Shumway and Stoffer 83), whereas ARIMAs can be more efficient because they integrate two components, an autoregressive factor and a moving average factor. The autoregressive factor regresses on past data to attempt to determine future data, while the moving average factor calculates the average of n year length subsets of the data. When these two factors are integrated, ARIMA models are able to map subtle trends and determine magnitude of these trends. Unlike linear/polynomial models, it is not attempting to explain the relationship between a specific independent and dependent variable. ARIMA models attempt to define trends over the time period that are represented in your data.

The testing of importance of a ARIMA model is slightly different than testing linear and polynomial regression models. To test a ARIMA model, the BIC and coefficient p-values were used to determine significance. BIC was primarily used to evaluate model strength, but coefficients' p-values were also examined in order to maintain some consistency amongst all three types of models. It was not straight forward to compare the results from ARIMA models with those of linear and polynomial models given utilizing BIC vs. R^2. However, given the fact that the R^2 values were low for both models, it was easy to conclude that they were insignificant.

There were clear differences in temperature variability between months for each site and across all sites. In particular, significantly more year-to-year variability in temperature was found for January relative to the other three months. In contrast, the least variable month was the warmest month, July. Not only was there more year-to-year variability in the winter, but the range in temperatures over all sites in January was much greater than that of July. Clear differences in metrics related to variability yield the conclusion that colder months (and thus, colder temperatures) are much more variable than warmer months (and warmer temperatures). In addition, temperature variability was related to distance from the ocean. In general, sites closer to the ocean had lower variability than those more inland. This means, that in the northeastern United States, models purporting both increases in temperature variability and increases in temperature are unlikely to be accurate when tested against raw data.

Findings from the current study, which are based on long-term data continuously collected from airports, is in stark contrast to other studies focused on the northeast region as well as individual northeastern states. Mecray et al. (2018), stated that the northeastern United States is warming at a faster rate than most of the United States. In their regional results, Mecray et al. (2018) reported that, "Increases in annual average temperatures [of] about 3°F [1.7°C] or more in New England since 1901." Although details are not provided, it is unlikely that the Mecray et al. (2018) study has continuous raw temperature data for each month and year dating back to 1901. Another study by Runkle et al. (2017) discussed temperature increases specifically in Rhode Island during a similar length of time as depicted in the Mecray et al. (2018) study. This Runkle et al. (2017) study stated, "Temperatures in Rhode Island have risen almost 4°F

(7.2°C) since the beginning of the 20th century." This study states that their pre-1950 data are also observed temperatures, meaning they were measured at the time, which brings into question the model they create. A model created by faulty data becomes a faulty model. It is unlikely that the data collected in Rhode Island pre-1950 is going to be as accurate/precise as the data that is currently being collected, nor consistently recorded from the same locality. In the current study, no data sets consisting of continuous temperature records from the same localities (e.g. airports) were uncovered that date to the early 1900's.

Despite the reliability of data sets purported older than 1950, the results from both the Mecray et al (2018) and Runkle et al. (2017) studies greatly deviate from findings reported in the current investigation. One site included in the current study from Warwick, RI, had continuous and consistent data across all months from 1950-2018. None of the metrics employed indicate results for the Warwick, R.I. site remotely similar to those purported by Runkle et al. (2017). When using a linear regression model run on each of the four months, none of them return increases in temperature even close to an increase of 7.2°C. In fact, for the month of January, a linear model returned a decrease in temperature of 0.94°C for the Warwick site over the last 69 years. These stark differences are important to note, as they form the basis of alarm and concern for citizens and politicians.

The Mercray et al. (2018) study, which also cites the work of Runkle et al. (2017), discussed potential impacts of a significant increase in temperature on different ecosystems. One of them, directly pertinent to the current study, is the potential impact of climate warming on freshwater lakes and water resources. The Mecray et al. (2018) study implies that, moving forward, freshwater habitats will face severe impacts from increases in temperature. It is important that all factors impacting a waterbody be considered when evaluating the health of the system. This relates to one of the problems outlined above, that issues in freshwater lakes are regularly defined as climate change impacts rather than including other potentially significant. What can only be viewed as an overestimated increase in temperature defined by Runkle et al. (2017) when compared with findings from the current study, is being purported as the most important driver causing change in freshwater lakes. This increases the likelihood of other variables that may be impacting freshwater lakes being overlooked, leading to more damage to these systems.

Given a lack of transparency (or description) in data sourcing and model parameters in both the Mecray et al. (2018) and Runkle et al. (2017), it was not possible to evaluate the root cause resulting in different conclusions regarding climate warming. It is possible that the temperature observations from their pre-1950 data are the cause of such stark differences. Lastly, it is notable that the ARIMA model used in the current study, which can be accurate in its predictability, also failed to yield significant increases in temperature.

While not reporting as significant of trends in temperature as Runkle et. al. (2017), Murray et al. (2021) reports significant increases in the mean average temperature at Mt. Washington in New Hampshire. They find warming temperatures as well across the entirety of the study period (1935-2018); their study finds approximately 0.10°C increase in temperature at the summit of Mt. Washington, a 0.17°C increase in temperature for the State of New Hampshire, and reports a 0.11°C increase in temperature for the entirety of the northeast. Although these temperature increases are slight compared to values reported in both the Mecray et al. (2018) and Runkle et al. (2017) reports, they still are contrary to conclusions made in the current study. What appears to be a significant difference in the Murray et al. (2021) study is based on linear regression. Their testing method for significance was a non-parametric Mann–

Kendall test, which they used to indicate significant trends, versus usage in this study of R^2 and p-values which yielded no linear trends over time. This transparency in testing and data sourcing allowed for a comparison of methods to potentially help to determine where divergence between the two studies.

The Mann-Kendall test is used to determine significance of trends (up, down or monotonic). This method of determining any increase in temperature does not determine the significance of linear regressions in the same way that temperature trends were evaluated in the current investigation. The significance tests in the current study focused on evaluating the significance of the regressions and determine how much of the variation in the data can be attributed to the models. While the Mann-Kendall is effective in that it does not require a linear relationship or a normal distribution, it is not able to determine the magnitude of change (by how much the trend increases/decreases). Their approach to identifying statistically significant trends is less efficient than how significance of a linear model was measured in the study done here (which would require a linear relationship between variables). In that they attempted to identify if there was a statistically significant change, then attempted to map that change without identifying if their mapping was significant or not. Our study also includes non-linear models, which were also utilized to test for non-linear relationships (like the Mann-Kendall test is able to). Thus, this allowed for a determination of trend significance over the time series, and the magnitude of any trend over time. Interestingly, Murray et al. (2021) found much more subtle increases in temperature than either the Runkle et al. (2017) and Mecray et al. (2018) studies. While they found a significant trend and an increase in temperature, due to the two different tests, it’s hard to determine if their increase in temperature is a trend or not. Lastly, it is important to note that the Murray et al. (2021) study is focused on New Hampshire while the current study covers a broader region, which could result in differences between the studies.

The lack of trends across the entirety of the time series dataset are all important to note, and are the larger message gleaned from the study. However, based on a subset of the data, a definitive cooling period was uncovered from 1950-1970. All three statistical analyses were used to test and confirm this trend. It is hard to specifically determine how significant the trend was because it is not uncommon for regressions run on smaller datasets to yield higher R^2 and BIC values. However, this again points to the importance of our coefficient p-values which were more significant for this cooling trend than they were with the entirety of the dataset. The cooling period is important and significant to note, as it is the likely reason that some studies report temperature in the northeastern United States to be increasing post the 1980s. The cooling trend identified between 1950 and the 1970's, which is just as significant as any warming post 1980 trend (if not more significant) shows that temperatures in the northeast have been fluctuating over the last seven decades and not necessarily consistently up or down.

The cooling period identified in this study was previously identified by scientists, and documented in the literature, for the contiguous United States. Mascioli et al. (2017) identified a cooling period in summertime temperatures in the northeast and southeast United States. In their study, they state, "significant summertime cooling occurs in the early 1950s to the mid-1970s, which partially is attributed to increasing anthropogenic aerosol emissions" (Mascoli et. al. 2017). Results of the current study also show significant summer cooling, but to a lessen degree than noted by Mascioli et al (2017), however, both studies reported a similar winter cooling event. However, the winter cooling period noted by Mascioli et al (2017) from 1950-1970 was not linked to aerosol emissions, unlike the summer cooling trend. The Mascioli et al. (2017)

study also concluded that it is extremely important to consider multiple variables when looking at extremely complex systems, such as climate. They recommend, that climate scientists include aerosols as an important variable in climate models and one that limits warming.

Although the current study did not detect any significant trends in temperature, up or down, it did uncover interesting insights related to temperature variability. Temperature variability for each month behaved slightly differently over the 69-year period. In general, there was significantly more variability during January than the other months studied, as depicted using standard error. The month of January had a standard error of 0.30 °C while July's standard error was around 0.12 °C. The range in mean average temperatures for all sites in January is much larger than that of July. For the month of January, the lowest recorded mean average was 8.83°C while the warmest was 0.77°C resulting in a range of 9.6 °C. In contrast, during July, the warmest mean average temperature was 24°C and the coldest was 19.15°C, resulting in a range of 4.85°C. This initially shows that colder months tend to have more variability than warmer months over the northeast. Further, when considering October and April, they both had standard errors lower than January, but higher than July. However, in this case, April is cooler than October (April's mean is 7.89°C, October's mean 10.72°C), and both months had a similar standard error (0.16 vs. 0.17). To summarize, yearly mean temperature during warmer months were generally less variable than cooler periods.

Further, year-to-year variability also was more apparent in the colder months than the warmer months. When analyzing year to year differences (e.x. temperature at 1951 – temperature at 1950) in January, there are, on average, significantly larger differences in winter. Regardless, no significant trends in variability over time were found, meaning that variability in temperature has not been increasing or decreasing over time.

To summarize, it is of utmost importance to consider other factors in addition to temperature and other climate-related variables when analyzing changes to local environments. Climate warming is not consistent across the globe, and assuming that it is may lead to false interpretations of changes in aquatic and terrestrial trends ecosystems being related to climate warming, that may not exist in a region. For the northeastern United States, no temperature trend(s) was detected over the period 1950-2018 for the months of January, April, July and October.

Conclusion:

Our study does not support previous findings that the temperature in the northeastern region of the United States has significantly increased since 1950. There was statistically significant variability at all sites during cold months which may be important to researchers to note. These findings contradict the notion that temperatures are going to both increase and become more variable as time goes on. Our data also further emphasizes the importance of proximity to the ocean with respect to temperature variability. While further north sites were colder and more variable, it was also seen that sites near the ocean were warmer and less variable than sites at similar latitudes. This trend will be important for models in the future to consider when looking at temperature trends over regions that include coastline. The coastal sites will most likely experience less temperature variability, and depending on ocean currents be warmer or colder, than sites situated at similar latitudes but further inland. In the future, additional analyses will be necessary to understand why the air temperature in the northeast is not increasing at rates observed in other parts of the country.

Figures and Tables:

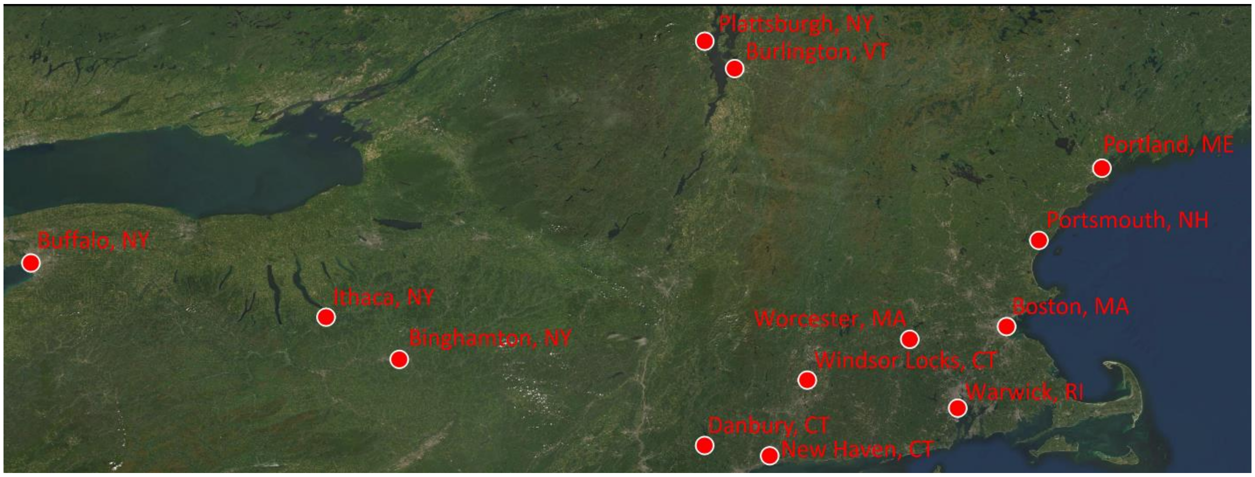

Figure 1: Map displaying the distribution of sites throughout the study region with labels identifying each site.

Table 1: The geographic coordinates of the 13 study sites.

Site	Latitude	Longitude	Site	Latitude	Longitude
Boston, MA	42.367	-71.022	**Portsmouth, NH**	43.072	-70.762
Buffalo, NY	42.886	-78.878	**Portland, ME**	43.661	-70.255
Binghamton, NY	42.099	-75.913	**Plattsburgh, NY**	44.699	-73.543
Burlington, VT	44.476	-73.212	**Warwick, RI**	41.700	-71.417
Danbury, CT	41.395	-73.454	**Windsor Locks, CT**	41.929	-72.627
Ithaca, NY	42.444	-76.502	**Worcester, MA**	42.263	-71.802
New Haven, CT	41.311	-72.929			

Table 2: Number of years out of 69 that mean temperature values were calculated for each of the four months (January, April, July and October) and each site used in this study.

Site	January	April	July	October
Binghamton, NY	69	69	69	69
Boston, MA	69	69	69	69
Buffalo, NY	69	68	69	69
Burlington, VT	69	69	69	69
Danbury, CT	61	66	63	64
Ithaca, NY	65	66	63	64
New Haven, CT	66	66	64	64
Plattsburgh, NY	50	51	51	50
Portland, ME	69	69	69	69
Portsmouth, NH	68	68	67	68
Warwick, RI	69	69	69	69
Windsor Locks, CT	69	69	69	69
Worcester, MA	68	69	69	68
Average	66	66	66	66

Table 3: Altitude in meters (m) of each of the airports that are associated with each of the cities that were used in this study.

Site	Altitude (m)	Site	Altitude (m)
Boston, MA	6.00	**Portsmouth, NH**	30.5
Buffalo, NY	221.9	**Portland, ME**	23.2
Binghamton, NY	439.7	**Plattsburgh, NY**	71.3
Burlington, VT	108.2	**Warwick, RI**	16.8
Danbury, CT	139.9	**Windsor Locks, CT**	52.7
Ithaca, NY	334.9	**Worcester, MA**	307.5
New Haven, CT	3.7	**Mean**	135.1

Table 4: Determination if sites are considered to be coastal based on being 10 km of the ocean.

Site	Ocean Front?	Site	Ocean Front?
Boston, MA	Yes	**Portsmouth, NH**	Yes
Buffalo, NY	No	**Portland, ME**	Yes
Binghamton, NY	No	**Plattsburgh, NY**	No
Burlington, VT	No	**Warwick, RI**	No
Danbury, CT	No	**Windsor Locks, CT**	No
Ithaca, NY	No	**Worcester, MA**	No
New Haven, CT	Yes		

Table 5: Averages of each temperature metric (mean minimum, mean average, mean maximum) for each site and month of the study period. Table also includes the average and range for each temperature metric across all sites for each month.

Site	January	April	July	October
Binghamton, NY	-15.7, -5.8, 5.8	-2.2, 6.8, 17.5	13.9, 19.8, 25.1	1.3, 9.2, 17.6
Boston, MA	-5, -1.4, 2.3	5, 9.1, 13.1	18.9, 23.1, 27.5	8.7, 12.5, 16.6
Buffalo, NY	-7.6, -4, -0.6	2.7, 7.6, 12.5	17, 21.8, 26.7	6.6, 10.3, 15.4
Burlington, VT	-11.9, -7.6, -3.1	1.4, 6.6, 11.8	15.9, 21.3, 26.8	4.7, 9.3, 13.9
Danbury, CT	-7, -2.7, 1.7	3.3, 9.1, 14.9	16.6, 22.2, 27.9	5.5, 11.1, 16.9
Ithaca, NY	-8.9, -4.8, -0.7	1.7, 7.2, 12.7	14.9, 20.9, 26.9	9.8, 10, 15.7
New Haven, CT	-10.1, -0.5, 7.9	3.2, 9.9, 17.4	17.6, 27.9, 29.8	5.9, 13.2, 20.1
Plattsburgh, NY	-19.9, -7.6, 3.8	-1.4, 6, 14.9	14.9, 20.4, 25.9	1.5, 8.5, 16.5
Portland, ME	-10, -5.4, -0.5	1.5, 6.4, 11.4	15.4, 20.5, 25.9	4.4, 9.7, 14.7
Portsmouth, NH	-8.1, -3.9, 0.3	2.9, 7.7, 12.5	16.6, 21.6, 26.8	5.9, 10.8, 15.7
Warwick, RI	-11.4, -1.5, 8.3	2.3, 8.9, 16.9	17.4, 22, 27.5	4.7, 11.7, 18.9
Windsor Locks, CT	-7.7, -3.3, 1.1	3.9, 9.6, 15.4	17.4, 23.1, 29	5.8, 11.5, 17.3
Worcester, MA	-8.2, -4.4, -0.5	2.8, 7.7, 12.6	16.7, 21.2, 25.9	5.9, 10.3, 14.7
Average	-10.1, -4.1, 1.9	2.1, 7.9, 14.1	16.4, 22.1, 26.9	5.4, 10.6, 16.5
Range	14.9, 7.1, 9	7.2, 3.9, 6.1	5, 8.1, 4.7	7.4, 4.7, 6.2

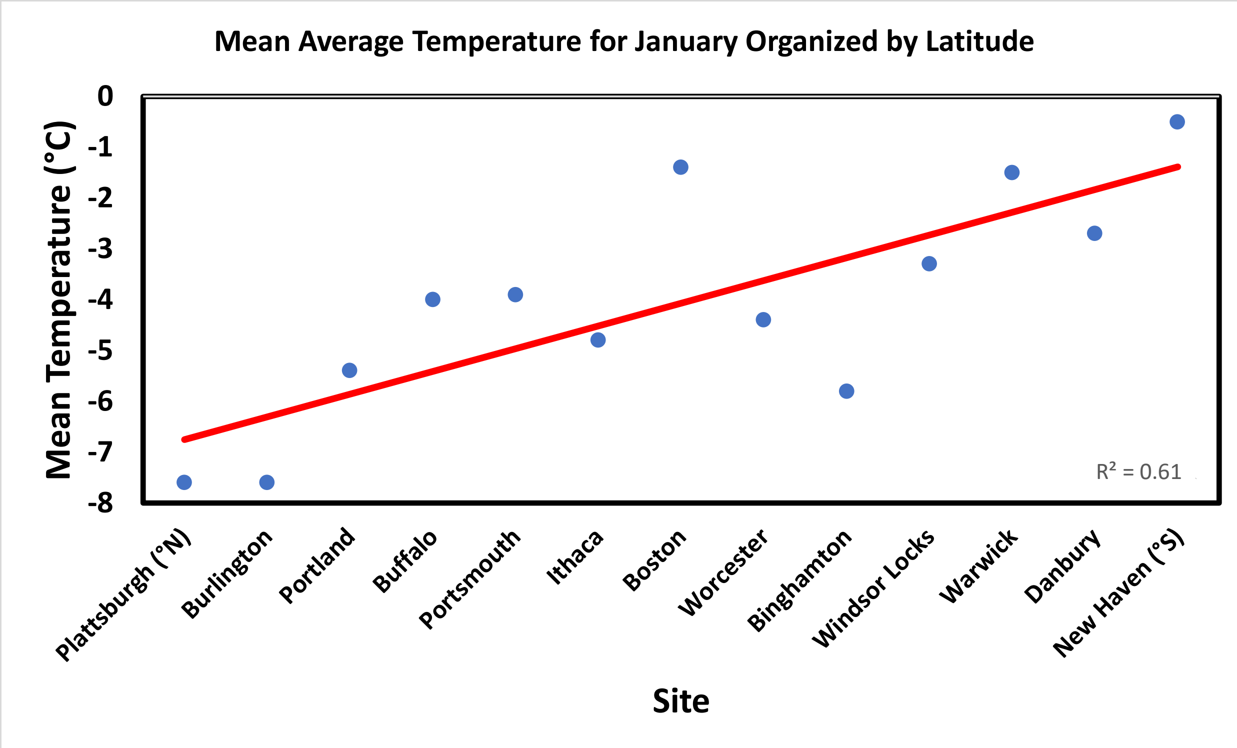

Figure 2: The mean temperature for each site during the month of January when organized by latitude. Sites decline in latitude along the x-axis. The red line is a linear regression illustrating the relationship between latitude and mean temperature.

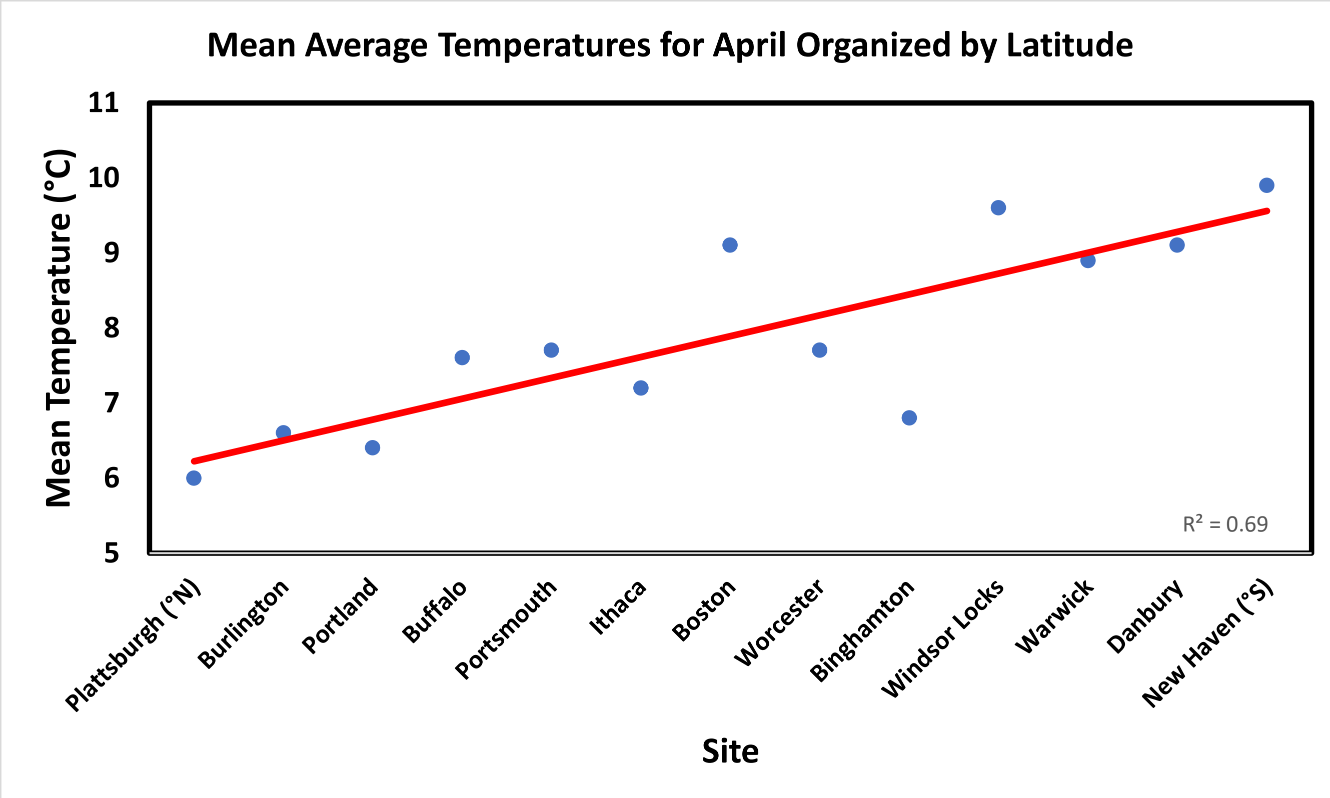

Figure 3: The mean temperature for each site during the month of April when organized by latitude. Sites decline in latitude along the x-axis. The red line is a linear regression illustrating the relationship between latitude and mean temperature.

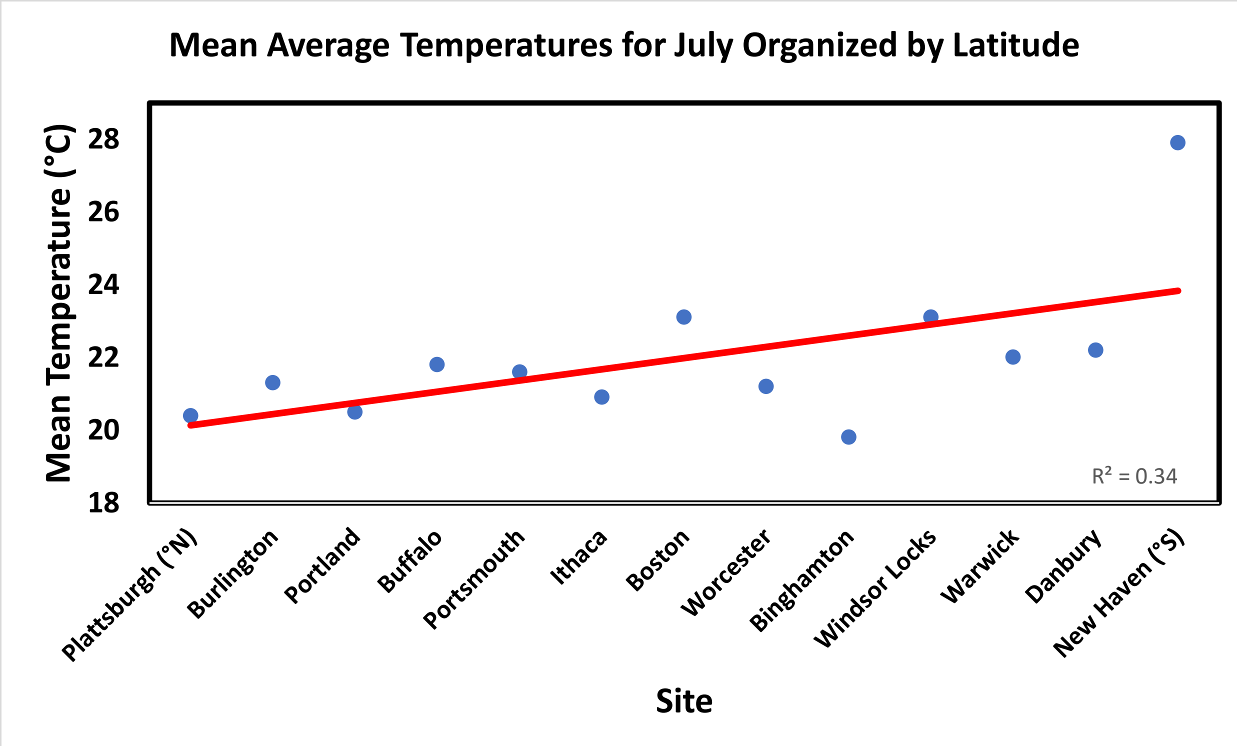

Figure 4: The mean temperature for each site during the month of July when organized by latitude. Sites decline in latitude along the x-axis. The red line is a linear regression illustrating the relationship between latitude and mean temperature.

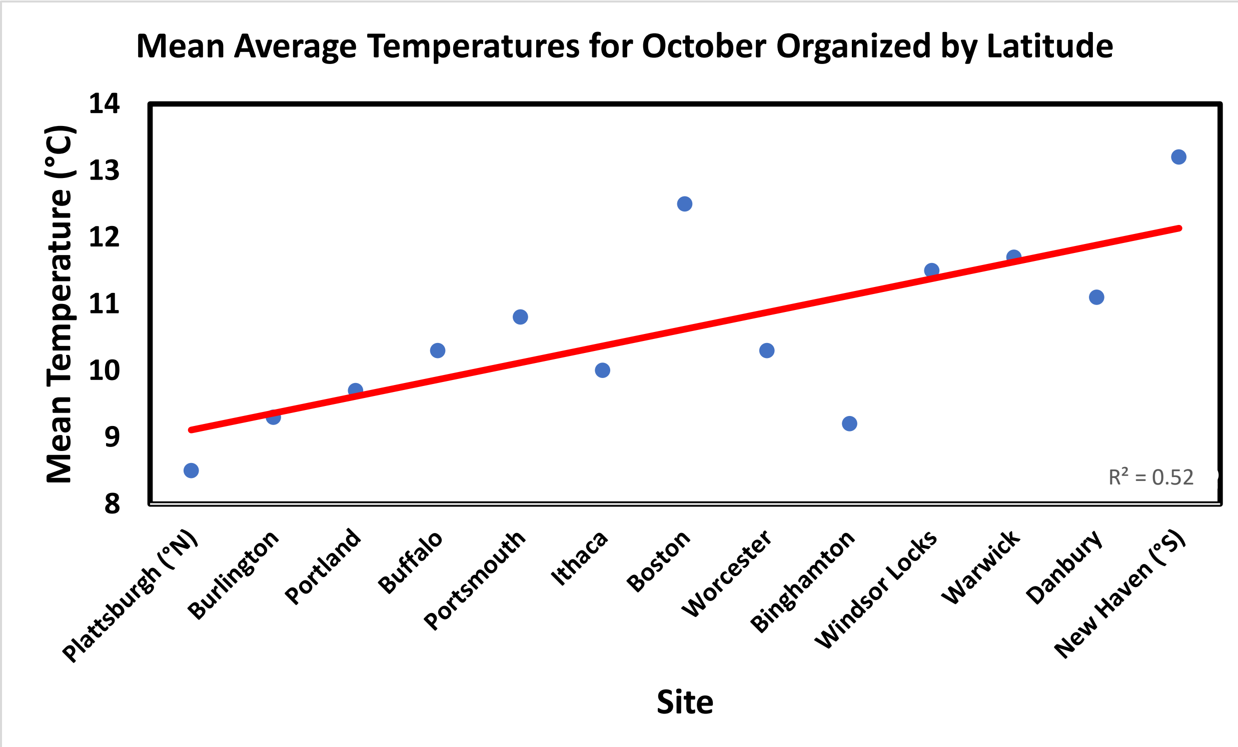

Figure 5: The mean temperature for each site during the month of October when organized by latitude. Sites decline in latitude along the x-axis. The red line is a linear regression illustrating the relationship between latitude and mean temperature.

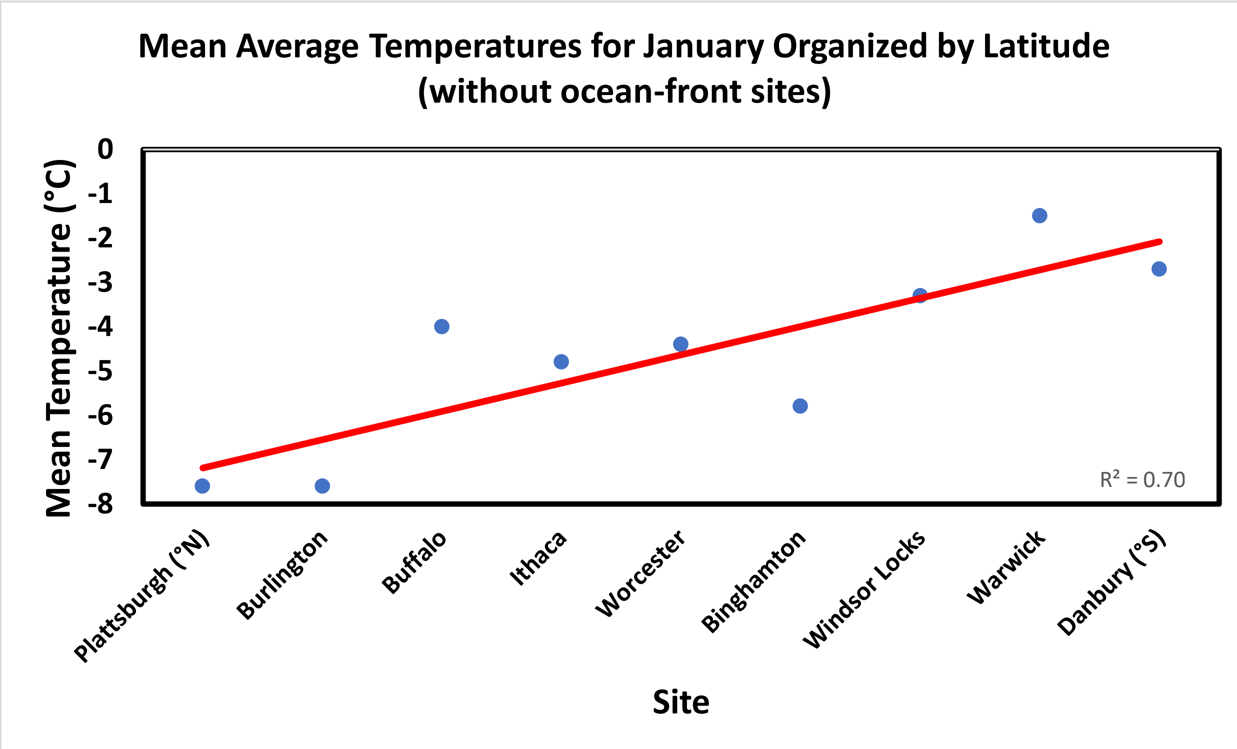

Figure 6: The mean temperature for each site during the month of January when organized by latitude and removing the ocean-front sites. Sites decline in latitude along the x-axis. The red line is a linear regression illustrating the relationship between latitude and mean temperature.

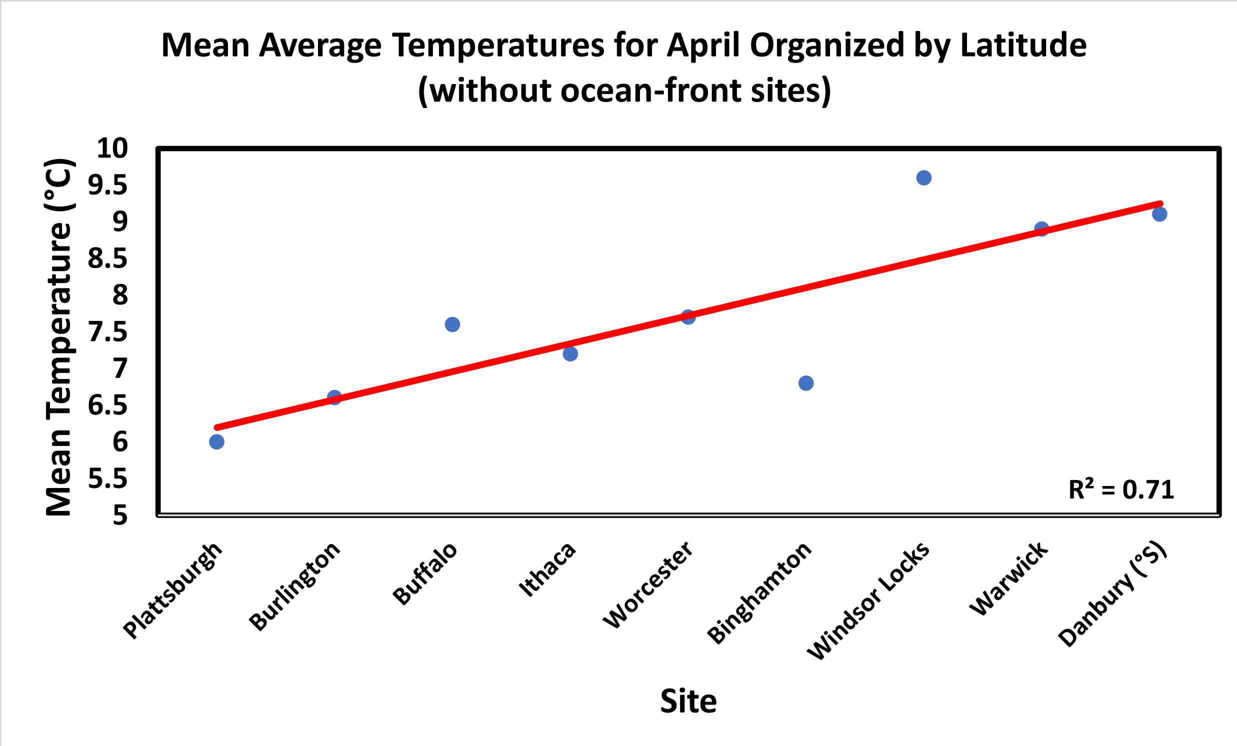

Figure 7: The mean temperature for each site during the month of April when organized by latitude and removing the ocean-front sites. Sites decline in latitude along the x-axis. The red line is a linear regression illustrating the relationship between latitude and mean temperature.

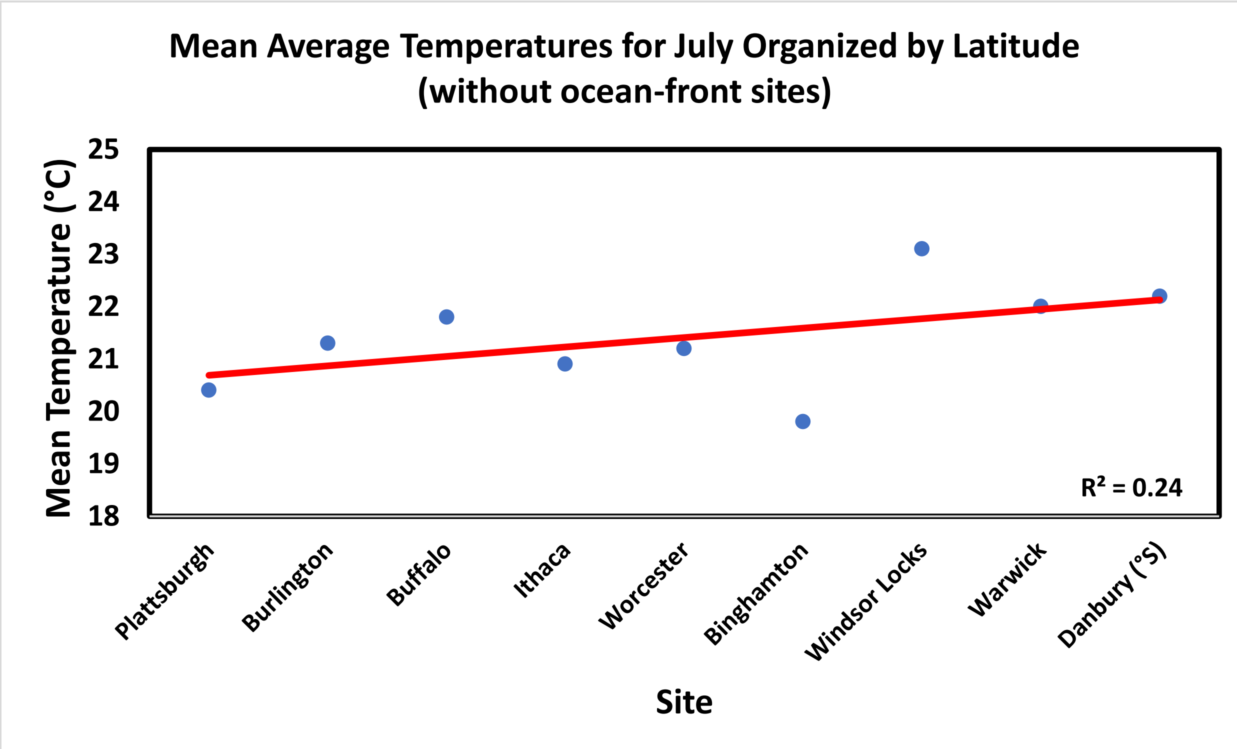

Figure 8: The mean temperature for each site during the month of July when organized by latitude and removing the ocean-front sites. Sites decline in latitude along the x-axis. The red line is a linear regression illustrating the relationship between latitude and mean temperature.

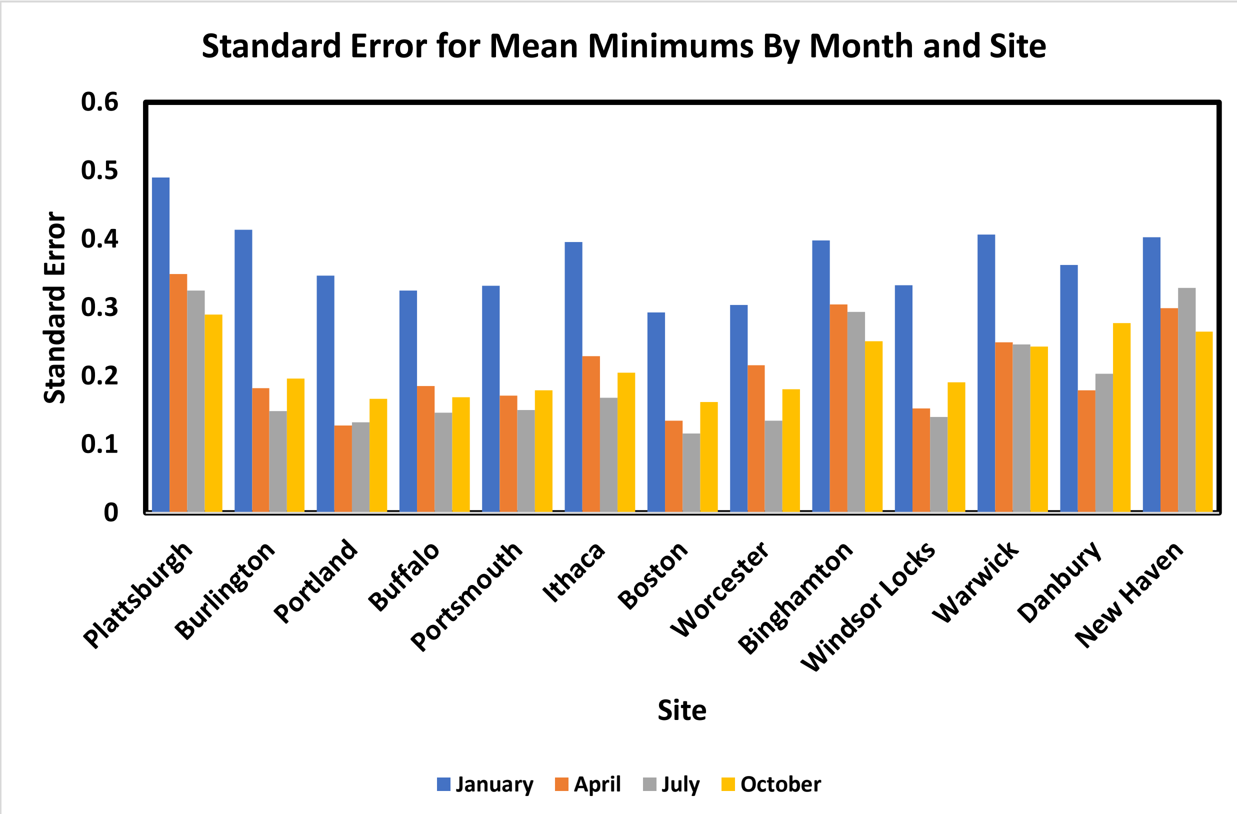

Figure 9: The standard error for each month at each site for the mean minimum temperature metric. Each bar represents a month for a site, which is listed on the x-axis.

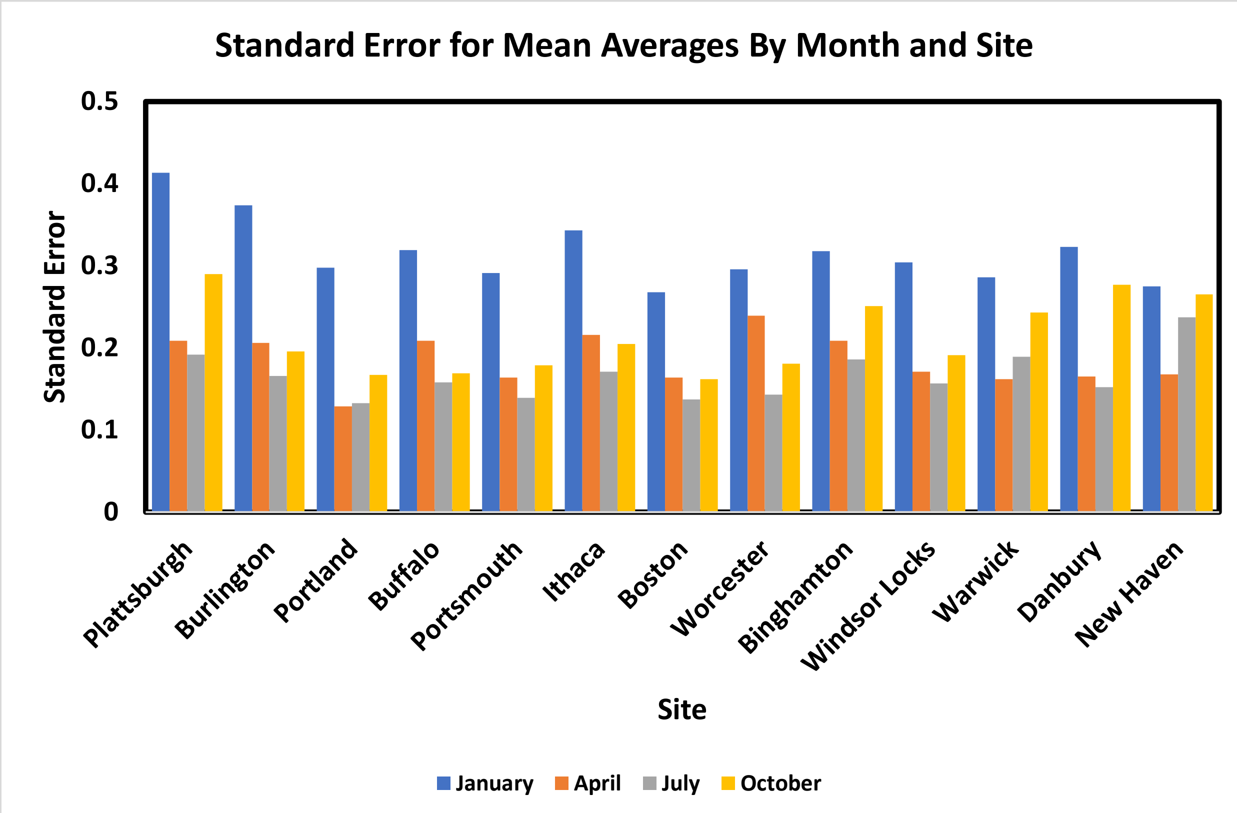

Figure 10: The standard error for each month at each site for the mean average temperature metric. Each bar represents a month for a site, which is listed on the x-axis.

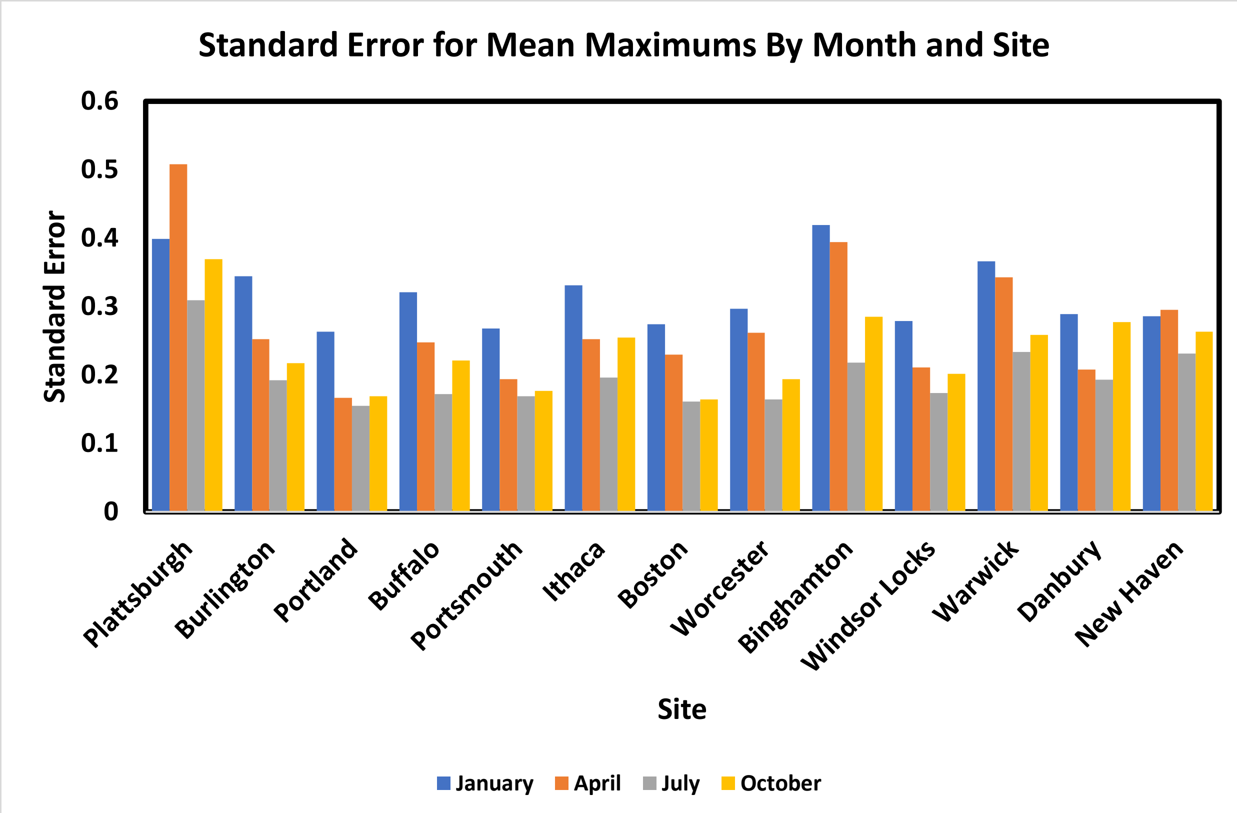

Figure 11: The standard error for each month at each site for the mean maximum temperature metric. Each bar represents a month for a site, which is listed on the x-axis.

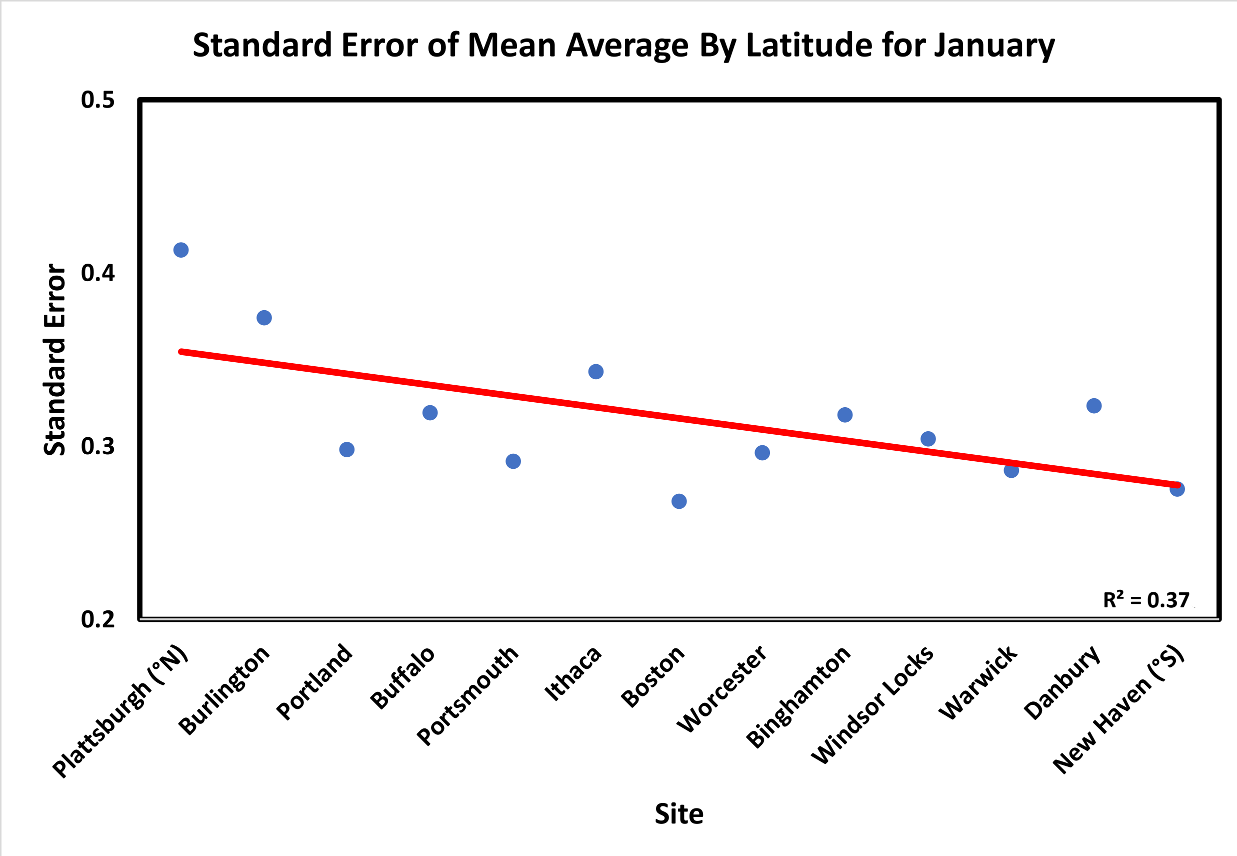

Figure 12: The relationship between the standard error for the mean average temperature metric and the latitude of the site for the month of January. Sites decline in latitude along the x-axis. The red line is a linear regression illustrating the relationship between latitude and mean temperature.

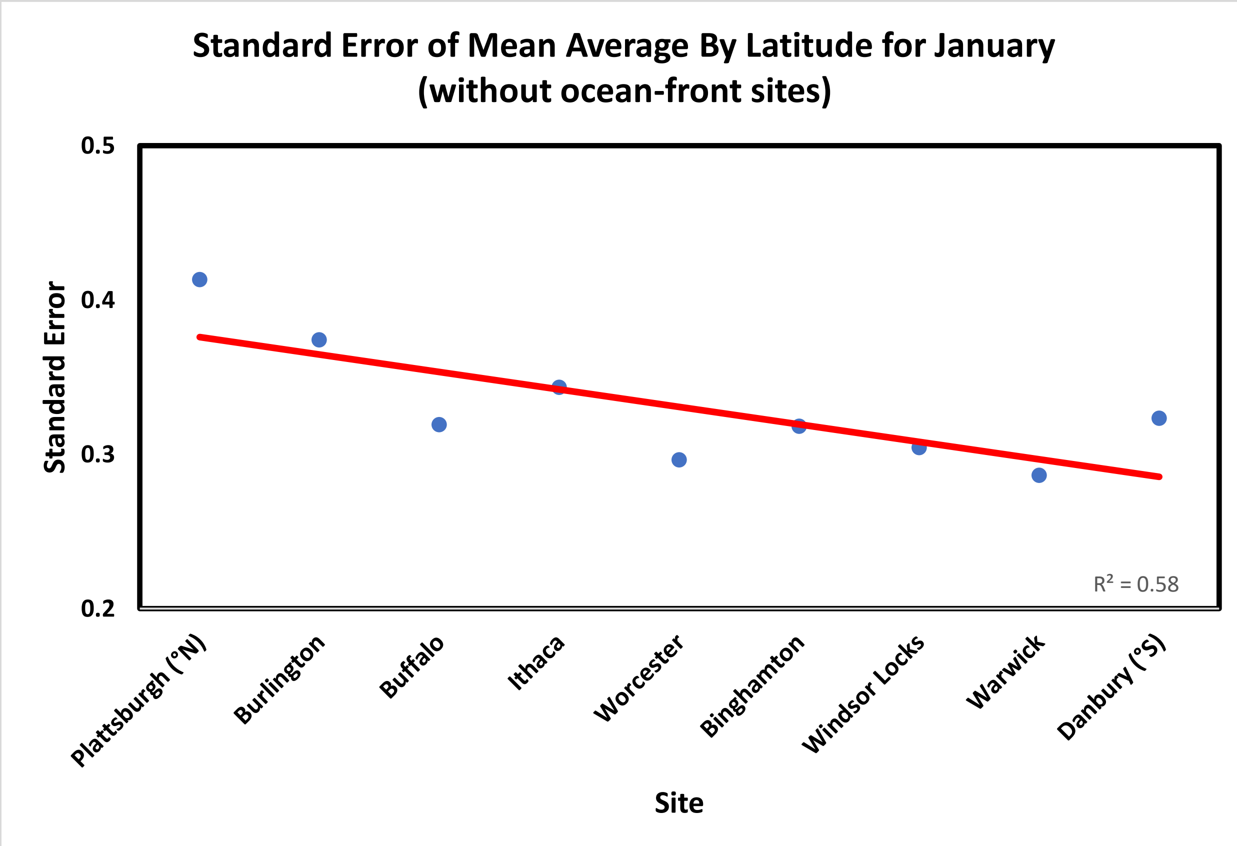

Figure 13: The relationship between the standard error for the mean average temperature metric and the latitude of the site for the month of January. Sites decline in latitude along the x-axis. The red line is a linear regression illustrating the relationship between latitude and mean temperature. In this figure, all sites that were defined as ocean-front sites have been removed.

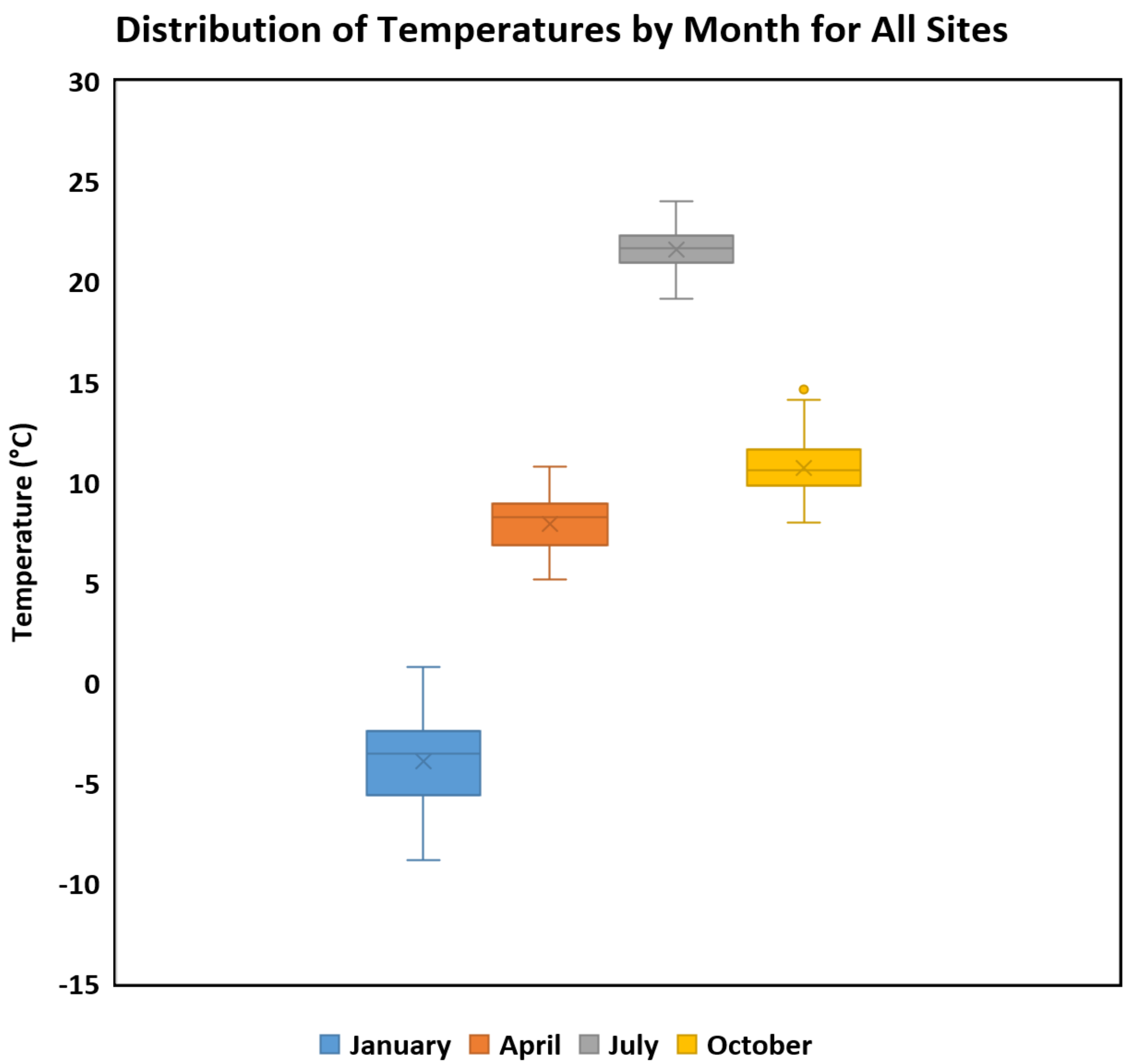

Figure 14: Box and whisker plot showing the distribution of mean temperatures by month for all sites. Each box and whisker represent mean average temperature for all sites for that individual month.

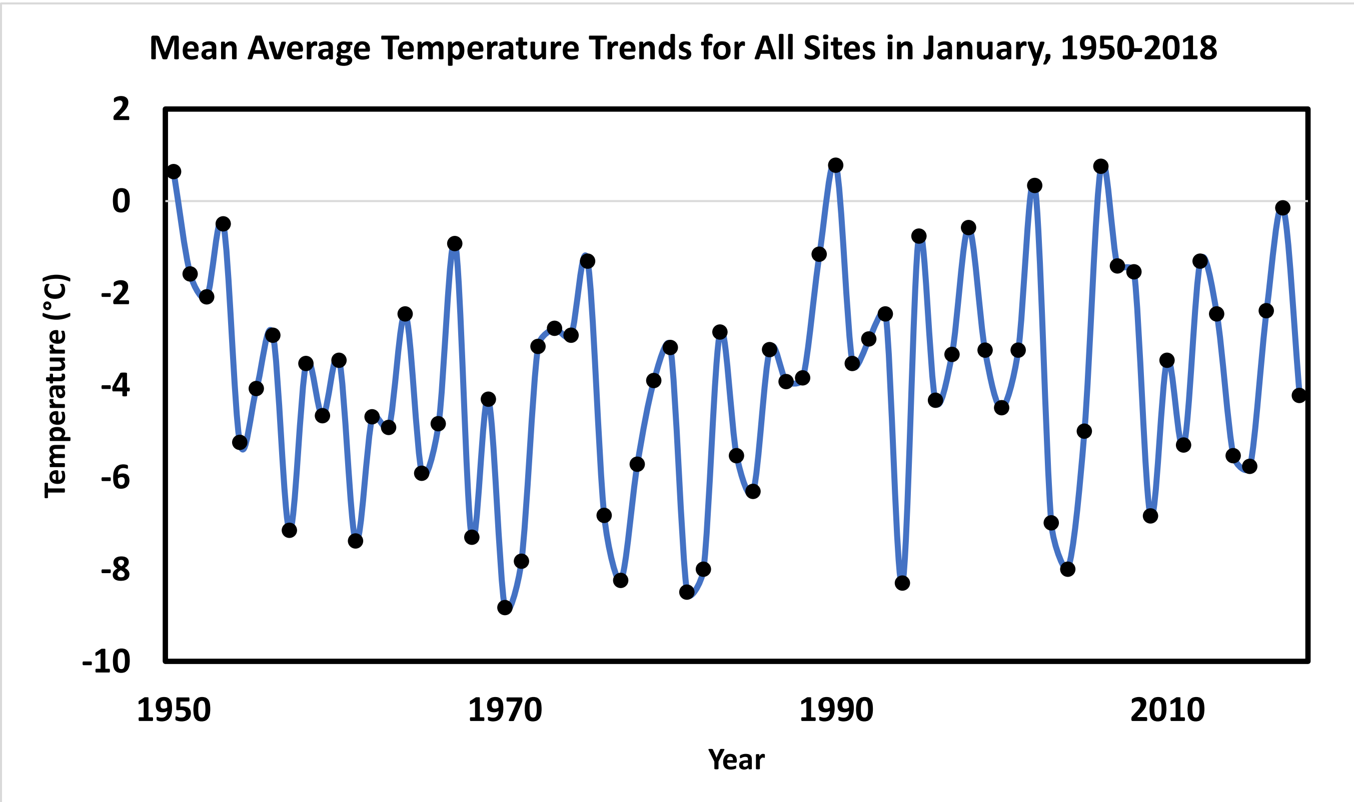

Figure 15: Line graph showing temperature trends for all sites for the mean average temperature metric for the month of January. This line is showing the average of all sites' mean average temperature metric for January.

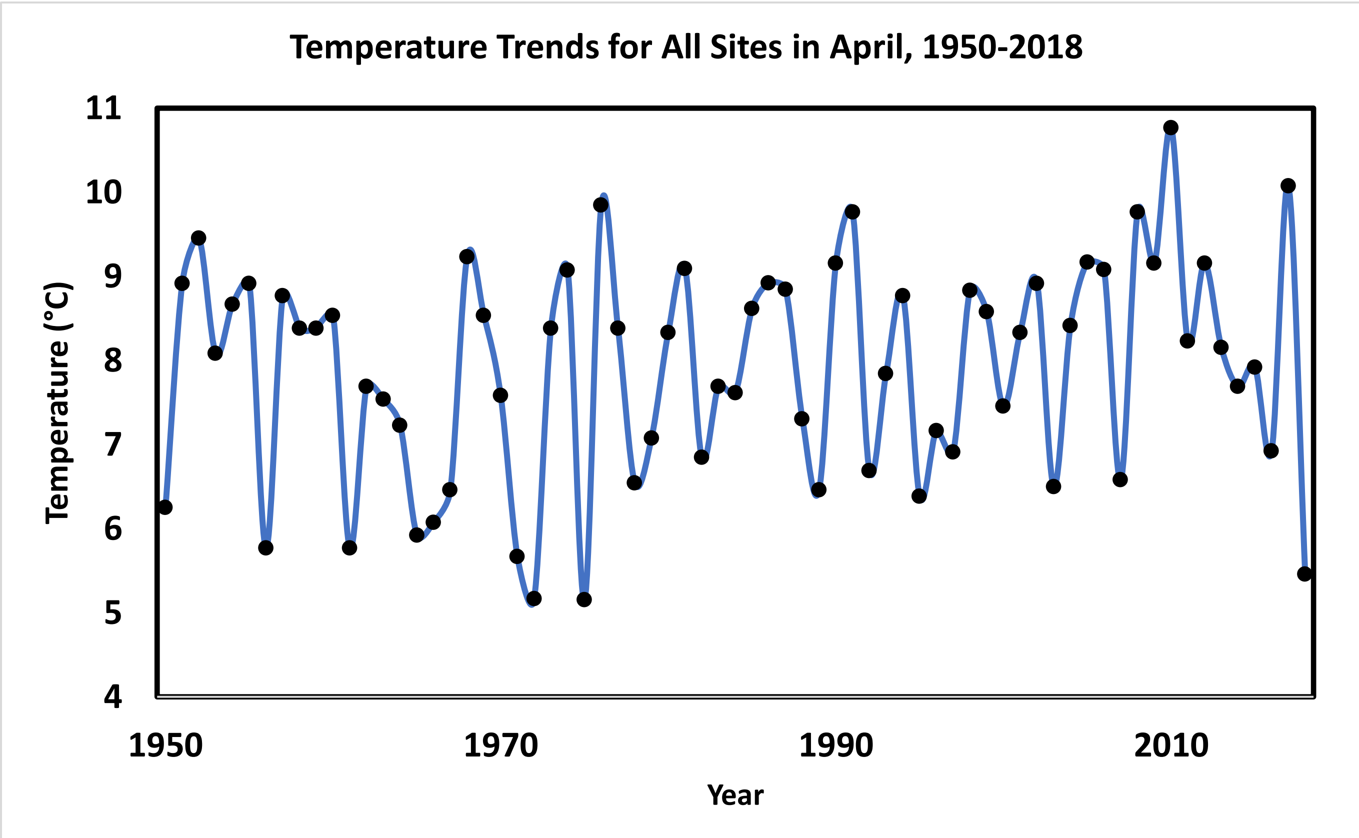

Figure 16: Line graph showing temperature trends for all sites for the mean average temperature metric for the month of April. This line is showing the average of all sites' mean average temperature metric for April.

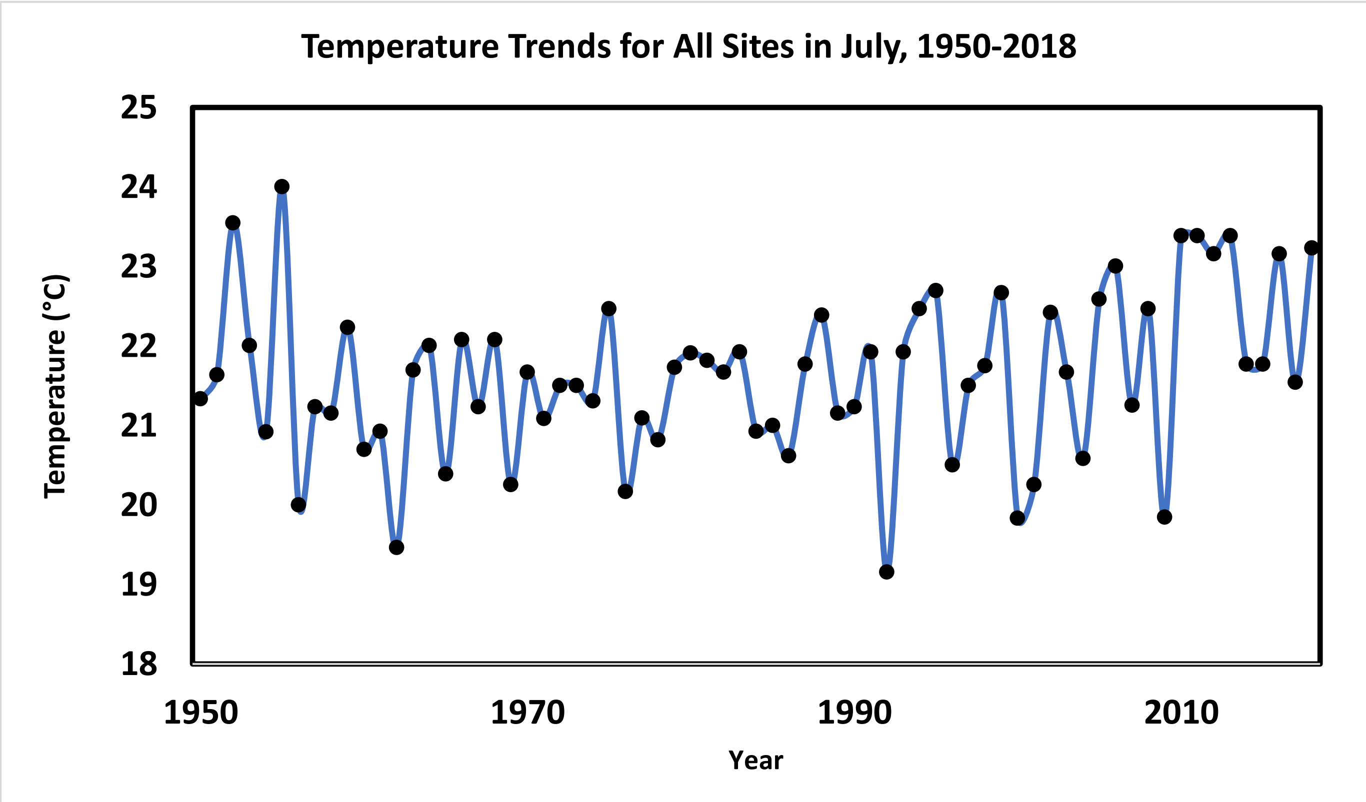

Figure 17: Line graph showing temperature trends for all sites for the mean average temperature metric for the month of July. This line is showing the average of all sites' mean average temperature metric for July.

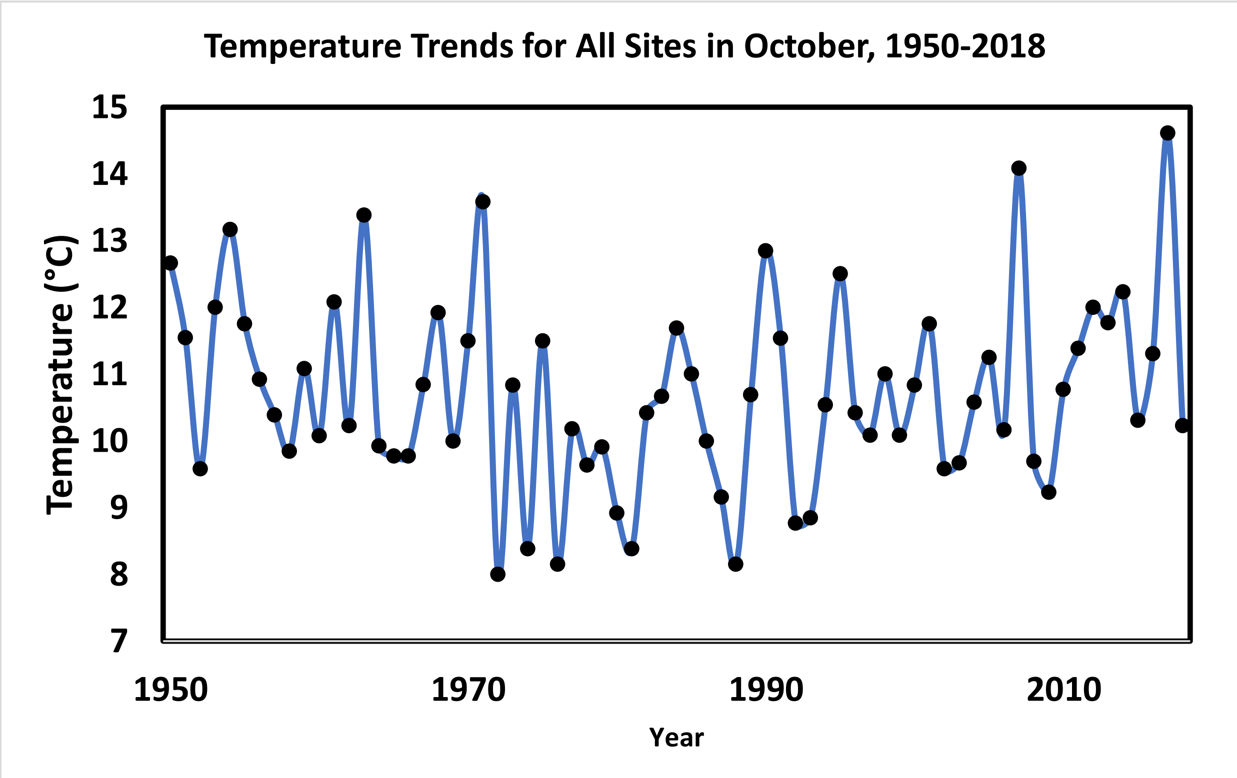

Figure 18: Line graph showing temperature trends for all sites for the mean average temperature metric for the month of October. This line is showing the average of all sites' mean average temperature metric for October.

Table 6: Metrics used to measure the significance of the linear regression analyses when run on the mean average temperature for each site. This table represents linear regressions only run on mean average temperature metrics for the month of January.

Site	R^2	P-Value	Site	R^2	P-Value
Binghamton, NY	0.007	0.49	**Plattsburgh, NY**	0.102	0.02
Boston, MA	0.009	0.45	**Portland, ME**	0.013	0.357
Buffalo, NY	0.002	0.67	**Portsmouth, NH**	0.0003	0.88
Burlington, VT	0.047	0.07	**Warwick, RI**	0.014	0.34
Danbury, CT	0.003	0.69	**Windsor Locks, CT**	0.015	0.316
Ithaca, NY	0.001	0.76	**Worcester, MA**	0.006	0.538
New Haven, CT	0.001	0.99			

Table 7: Metrics used to measure the significance of the linear regression analyses when run on the mean average temperature for each site. This table represents linear regressions only run on mean average temperature metrics for the month of April.

Site	R^2	P-Value	Site	R^2	P-Value
Binghamton, NY	0.008	0.46	**Plattsburgh, NY**	0.04	0.157
Boston, MA	0.029	0.16	**Portland, ME**	0.107	0.006
Buffalo, NY	0.016	0.31	**Portsmouth, NH**	0.005	0.58
Burlington, VT	0.099	0.008	**Warwick, RI**	0.039	0.10
Danbury, CT	0.0001	0.93	**Windsor Locks, CT**	0.038	0.11
Ithaca, NY	0.0001	0.95	**Worcester, MA**	0.072	0.025
New Haven, CT	0.011	0.41			

Table 8: Metrics used to measure the significance of the linear regression analyses when run on the mean average temperature for each site. This table represents linear regressions only run on mean average temperature metrics for the month of July.

Site	R^2	P-Value	Site	R^2	P-Value
Binghamton, NY	0.0002	0.92	**Plattsburgh, NY**	0.033	0.20
Boston, MA	0.049	0.07	**Portland, ME**	0.164	0.001
Buffalo, NY	0.041	0.09	**Portsmouth, NH**	0.009	0.458
Burlington, VT	0.171	0.001	**Warwick, RI**	0.049	0.065
Danbury, CT	0.035	0.142	**Windsor Locks, CT**	0.092	0.011
Ithaca, NY	0.017	0.303	**Worcester, MA**	0.062	0.04
New Haven, CT	0.0001	0.968			

Table 9: Metrics used to measure the significance of the linear regression analyses when run on the mean average temperature for each site. This table represents linear regressions only run on mean average temperature metrics for the month of October.

Site	R^2	P-Value	Site	R^2	P-Value
Binghamton, NY	0.012	0.37	**Plattsburgh, NY**	0.006	0.59
Boston, MA	0.004	0.59	**Portland, ME**	0.056	0.05
Buffalo, NY	0.0001	0.96	**Portsmouth, NH**	0.005	0.581
Burlington, VT	0.039	0.10	**Warwick, RI**	0.028	0.17
Danbury, CT	0.003	0.68	**Windsor Locks, CT**	0.006	0.521
Ithaca, NY	0.007	0.49	**Worcester, MA**	0.0003	0.898
New Haven, CT	0.016	0.32			

Table 10: Polynomial regression testing metrics for the month of January, the table shows the metrics used to measure the significance of the polynomial regression when run on the mean average temperature metric for each site. Significant coefficients (Sig Coeffs) represents the number of significant coefficients for each polynomial regression. Because a 6th order polynomial was used, the maximum number of significant coefficients is 6 (ignoring the y-intercept).

Site	R^2	Sig Coeffs	Site	R^2	Sig Coeffs
Binghamton, NY	0.015	0	**Plattsburgh, NY**	0.103	0
Boston, MA	0.04	0	**Portland, ME**	0.078	6
Buffalo, NY	0.049	0	**Portsmouth, NH**	0.045	0
Burlington, VT	0.096	0	**Warwick, RI**	0.072	0
Danbury, CT	0.005	0	**Windsor Locks, CT**	0.056	0
Ithaca, NY	0.005	0	**Worcester, MA**	0.057	0
New Haven, CT	0.019	0			

Table 11: Polynomial regression testing metrics for the month of April, the table shows the metrics used to measure the significance of the polynomial regression when run on the mean average temperature metric for each site. Significant coefficients (Sig Coeffs) represents the number of significant coefficients for each polynomial regression. Because a 6th order polynomial was used, the maximum number of significant coefficients is 6 (ignoring the y-intercept).

Site	R^2	Sig Coeffs	Site	R^2	Sig Coeffs
Binghamton, NY	0.026	0	**Plattsburgh, NY**	0.049	0
Boston, MA	0.037	0	**Portland, ME**	0.131	0
Buffalo, NY	0.016	0	**Portsmouth, NH**	0.032	0
Burlington, VT	0.103	0	**Warwick, RI**	0.112	6
Danbury, CT	0.001	0	**Windsor Locks, CT**	0.038	0
Ithaca, NY	0.004	0	**Worcester, MA**	0.074	0
New Haven, CT	0.011	0			

Table 12: Polynomial regression testing metrics for the month of July, the table shows the metrics used to measure the significance of the polynomial regression when run on the mean average temperature metric for each site. Significant coefficients (Sig Coeffs) represents the number of significant coefficients for each polynomial regression. Because a 6th order polynomial was used, the maximum number of significant coefficients is 6 (ignoring the y-intercept).

Site	R^2	Sig Coeffs	Site	R^2	Sig Coeffs
Binghamton, NY	0.207	5	**Plattsburgh, NY**	0.067	0
Boston, MA	0.094	0	**Portland, ME**	0.187	0
Buffalo, NY	0.059	0	**Portsmouth, NH**	0.049	0
Burlington, VT	0.21	0	**Warwick, RI**	0.28	6
Danbury, CT	0.038	0	**Windsor Locks, CT**	0.113	0
Ithaca, NY	0.029	0	**Worcester, MA**	0.125	6
New Haven, CT	0.124	6			

Table 13: Polynomial regression testing metrics for the month of October, the table shows the metrics used to measure the significance of the polynomial regression when run on the mean average temperature metric for each site. Significant coefficients (Sig Coeffs) represents the number of significant coefficients for each polynomial regression. Because a 6th order polynomial was used, the maximum number of significant coefficients is 6 (ignoring the y-intercept).

Site	R^2	Sig Coeffs	Site	R^2	Sig Coeffs
Binghamton, NY	0.214	6	**Plattsburgh, NY**	0.179	6
Boston, MA	0.104	6	**Portland, ME**	0.126	6
Buffalo, NY	0.083	6	**Portsmouth, NH**	0.086	6
Burlington, VT	0.171	6	**Warwick, RI**	0.279	6
Danbury, CT	0.054	0	**Windsor Locks, CT**	0.078	6
Ithaca, NY	0.049	0	**Worcester, MA**	0.089	6
New Haven, CT	0.197	6			

Table 14: ARIMA model testing metrics for the month of January, the table shows the metrics used to measure the significance of an ARIMA model when run on the mean average temperature metric for each site. The BIC represents the Bayesian Information Criterion of the model, and the Sig. Coeffs. column represents the number of significant predictors in the ARIMA model.

Site	BIC	Sig Coeffs	Site	BIC	Sig Coeffs
Binghamton, NY	338.21	3/3	**Plattsburgh, NY**	270.12	2/2
Boston, MA	313.68	2/2	**Portland, ME**	328.24	2/2
Buffalo, NY	337.96	2/2	**Portsmouth, NH**	319.35	2/2
Burlington, VT	359.58	2/2	**Warwick, RI**	322.57	2/2
Danbury, CT	293.39	2/2	**Windsor Locks, CT**	331.2	2/2
Ithaca, NY	323.97	2/2	**Worcester, MA**	321.90	2/2
New Haven, CT	300.88	1/2			

Table 15: ARIMA model testing metrics for the month of April, the table shows the metrics used to measure the significance of an ARIMA model when run on the mean average temperature metric for each site. The BIC represents the Bayesian Information Criterion of the model, and the Sig. Coeffs. column represents the number of significant predictors in the ARIMA model.

Site	BIC	Sig Coeffs	Site	BIC	Sig Coeffs
Binghamton, NY	279.27	2/2	**Plattsburgh, NY**	193.29	2/2
Boston, MA	245.55	2/2	**Portland, ME**	212.43	2/2
Buffalo, NY	274.96	2/2	**Portsmouth, NH**	241.87	2/2
Burlington, VT	273.40	2/2	**Warwick, RI**	243.95	2/2
Danbury, CT	233.13	2/2	**Windsor Locks, CT**	251.51	2/2
Ithaca, NY	268.81	2/2	**Worcester, MA**	302.35	2/4
New Haven, CT	235.79	2/2			

Table 16: ARIMA model testing metrics for the month of July, the table shows the metrics used to measure the significance of an ARIMA model when run on the mean average temperature metric for each site. The BIC represents the Bayesian Information Criterion of the model, and the Sig. Coeffs. column represents the number of significant predictors in the ARIMA model.

Site	BIC	Sig Coeffs	Site	BIC	Sig Coeffs
Binghamton, NY	267.36	4/4	**Plattsburgh, NY**	186.31	2/3
Boston, MA	221.49	2/2	**Portland, ME**	215.35	4.5
Buffalo, NY	241.15	2/2	**Portsmouth, NH**	214.87	2/2
Burlington, VT	251.65	3/5	**Warwick, RI**	243.64	2/2
Danbury, CT	209.95	2/2	**Windsor Locks, CT**	238.29	2/2
Ithaca, NY	224.46	2/2	**Worcester, MA**	225.84	2/2
New Haven, CT	270.94	2/2			

Table 17: ARIMA model testing metrics for the month of October, the table shows the metrics used to measure the significance of an ARIMA model when run on the mean average temperature metric for each site. The BIC represents the Bayesian Information Criterion of the model, and the Sig. Coeffs. column represents the number of significant predictors in the ARIMA model.

Site	BIC	Sig Coeffs	Site	BIC	Sig Coeffs
Binghamton, NY	302.81	2/2	**Plattsburgh, NY**	198.29	2/2
Boston, MA	241.98	2/2	**Portland, ME**	251.78	2/2
Buffalo, NY	264.29	2/2	**Portsmouth, NH**	236.39	2/2
Burlington, VT	263.72	2/2	**Warwick, RI**	241.74	2/2
Danbury, CT	279.94	2/3	**Windsor Locks, CT**	258.43	2/2
Ithaca, NY	254.08	2/2	**Worcester, MA**	265.21	2/2
New Haven, CT	233.75	2/3			

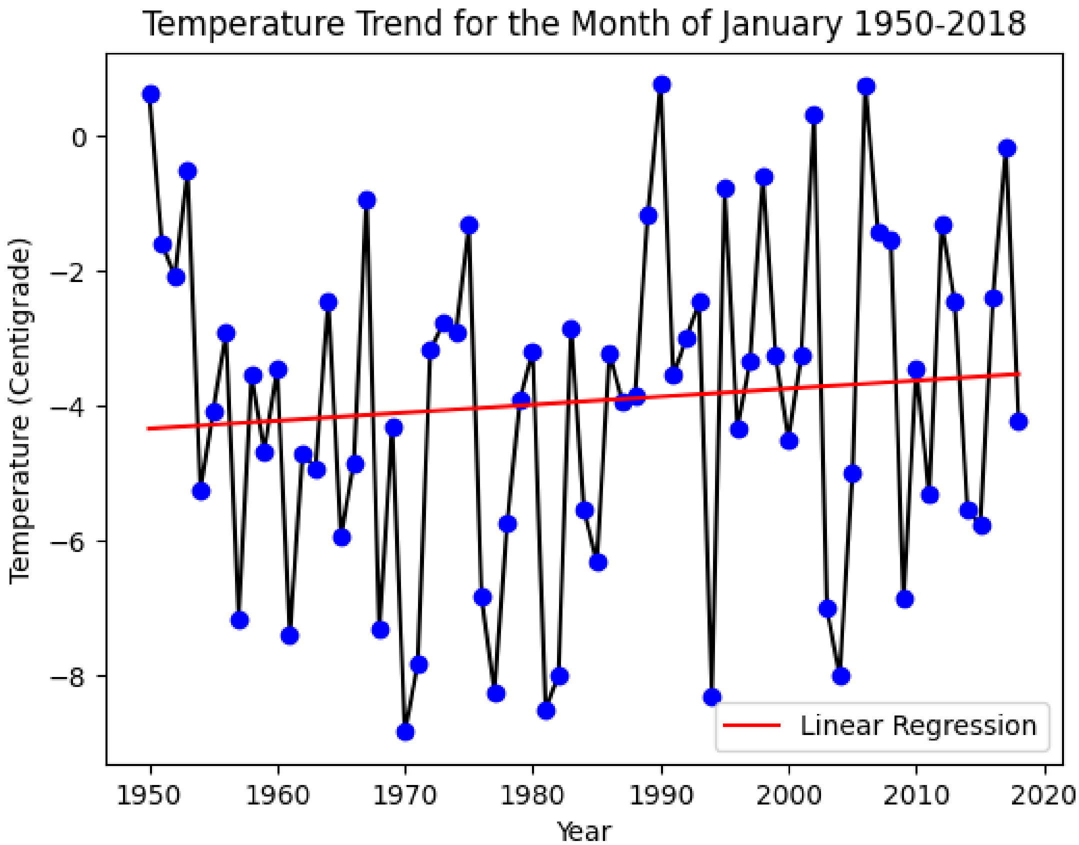

Figure 19: The change in mean temperature metric versus year for the month of January as the average of all sites. The red line is the linear regression model run on the data to find any linear trends in temperature.

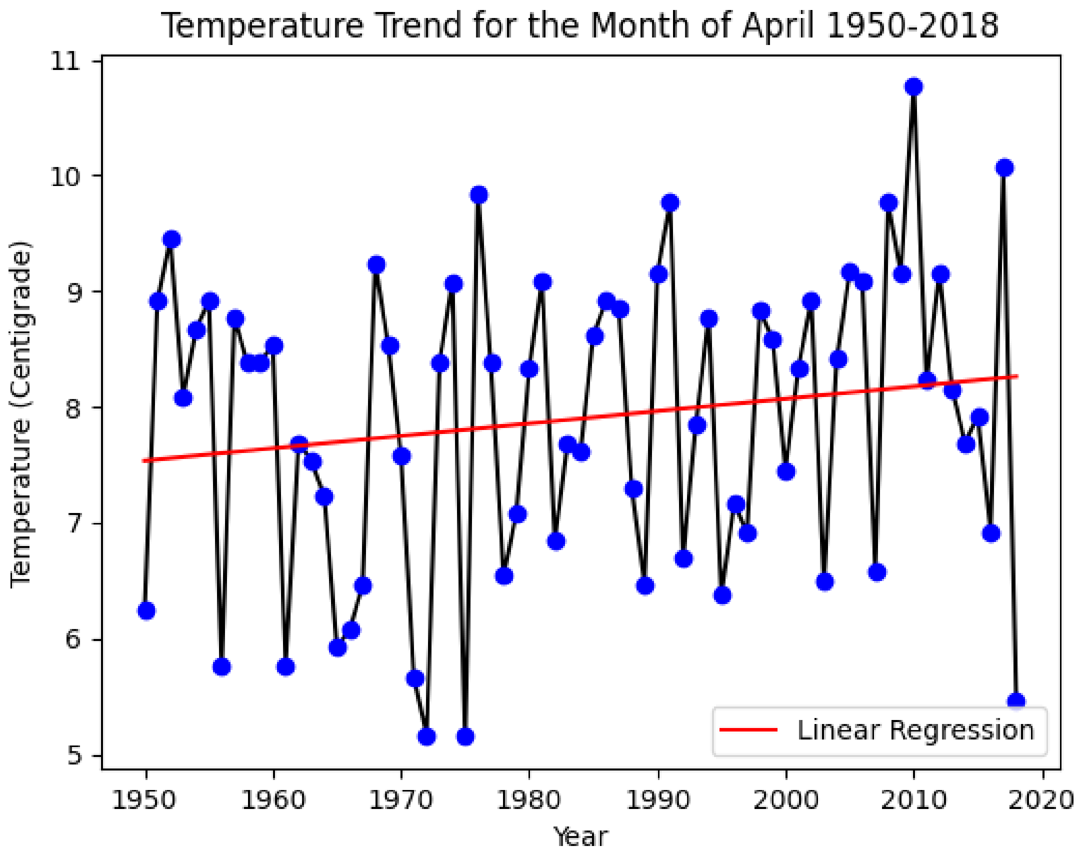

Figure 20: The change in mean temperature metric versus year for the month of April as an the average of all sites. The red line is the linear regression model run on the data to find any linear trends in temperature.

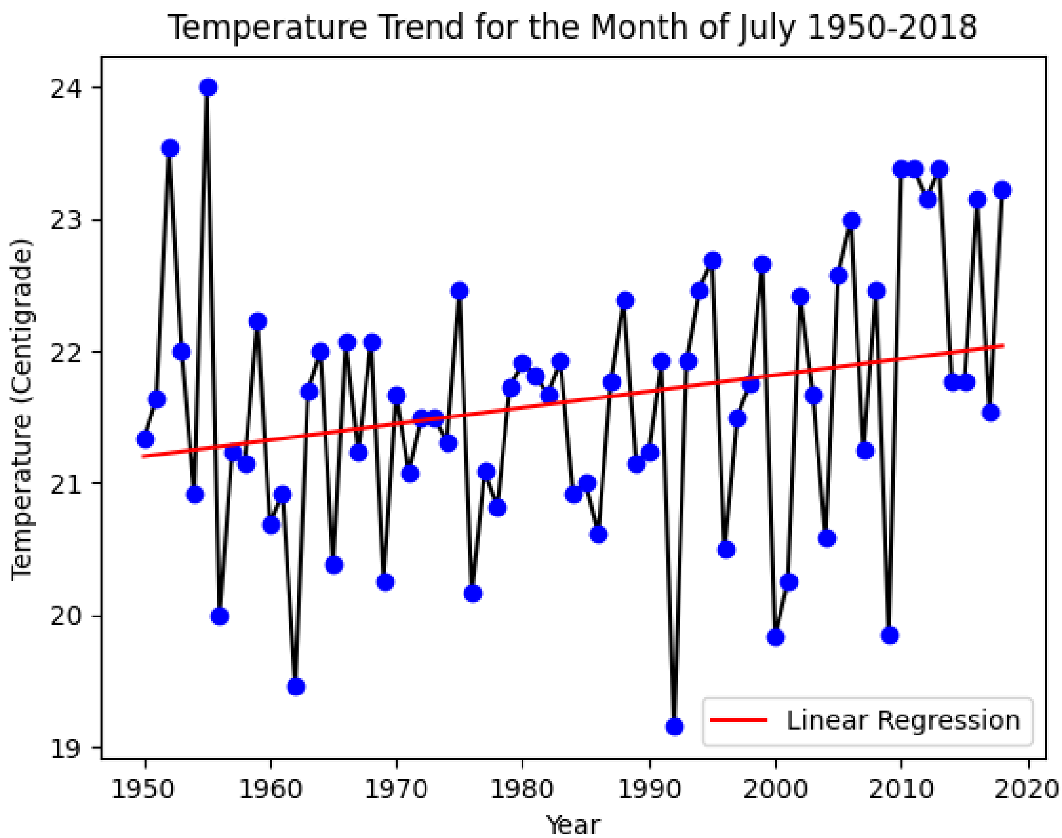

Figure 21: The change in mean temperature metric versus year for the month of July as an the average of all sites. The red line is the linear regression model run on the data to find any linear trends in temperature.

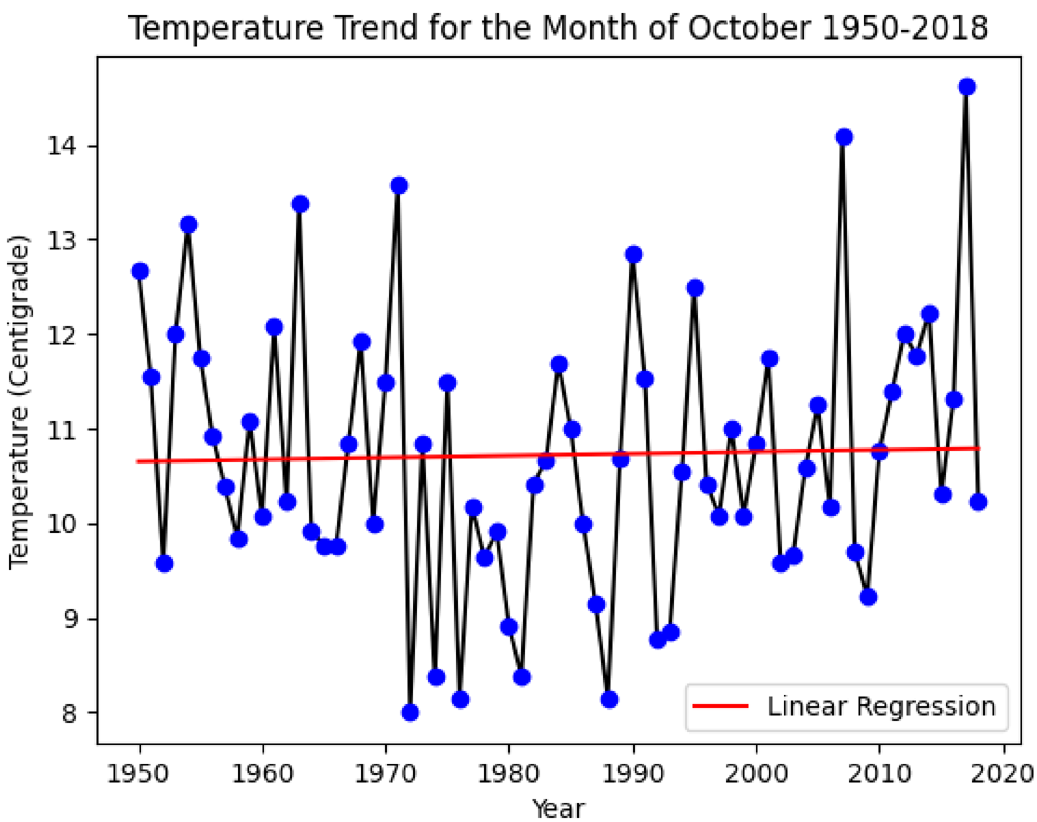

Figure 22: The change in mean temperature metric versus year for the month of October as an the average of all sites. The red line is the linear regression model run on the data to find any linear trends in temperature.

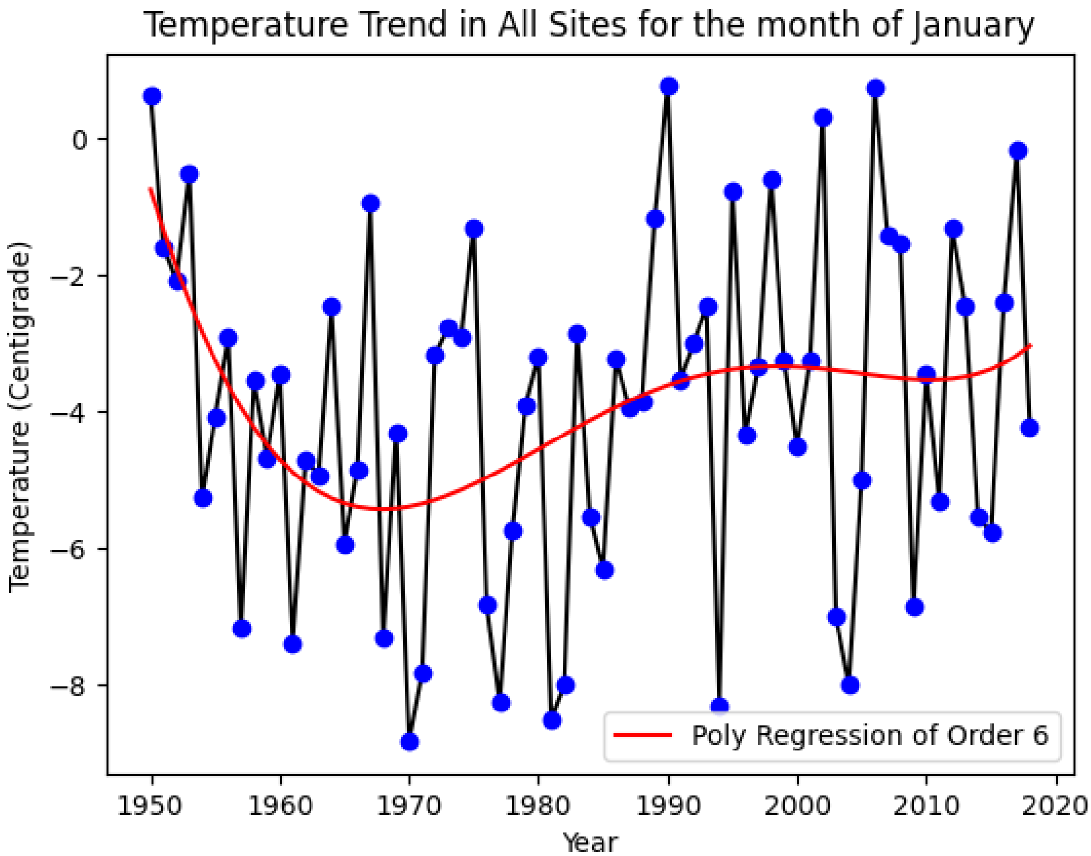

Figure 23: The change in mean temperature metric for the month of January for the average of all sites. The red line is the polynomial regression model run on the data to find any non-linear trends in temperature.

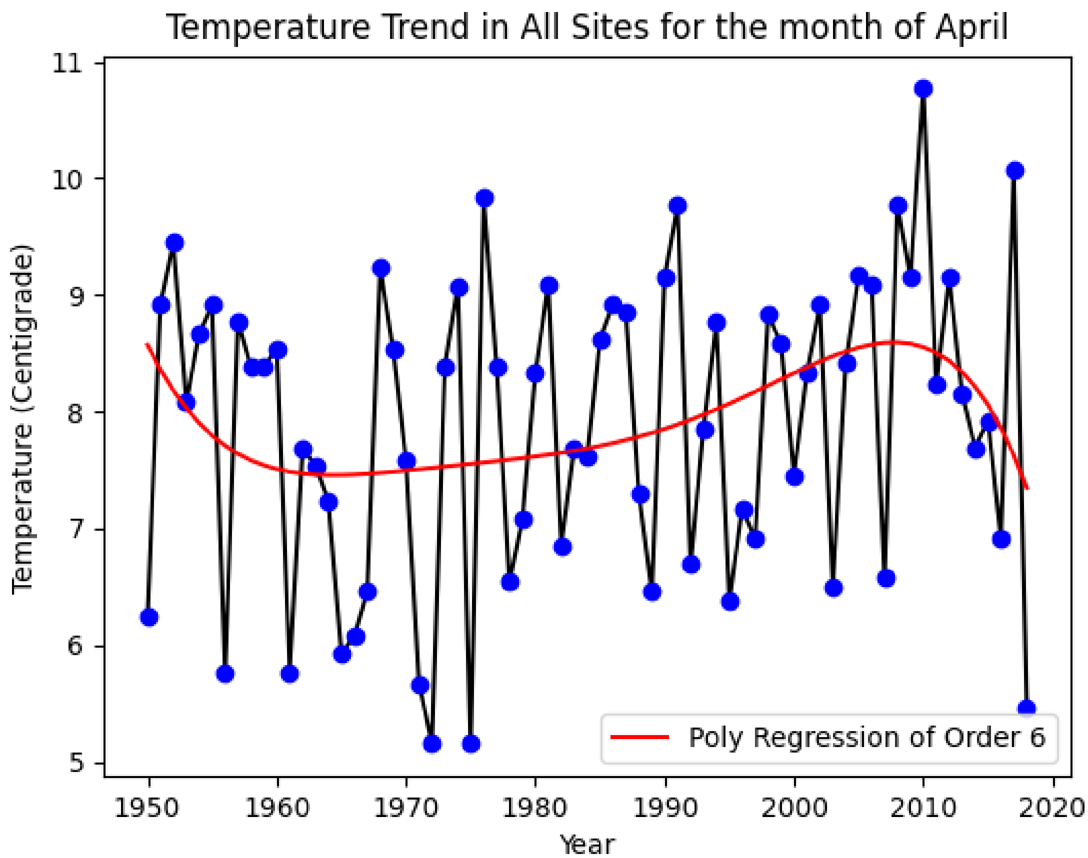

Figure 24: The change in mean temperature metric for the month of April for the average of all sites. The red line is the polynomial regression model run on the data to find any non-linear trends in temperature.

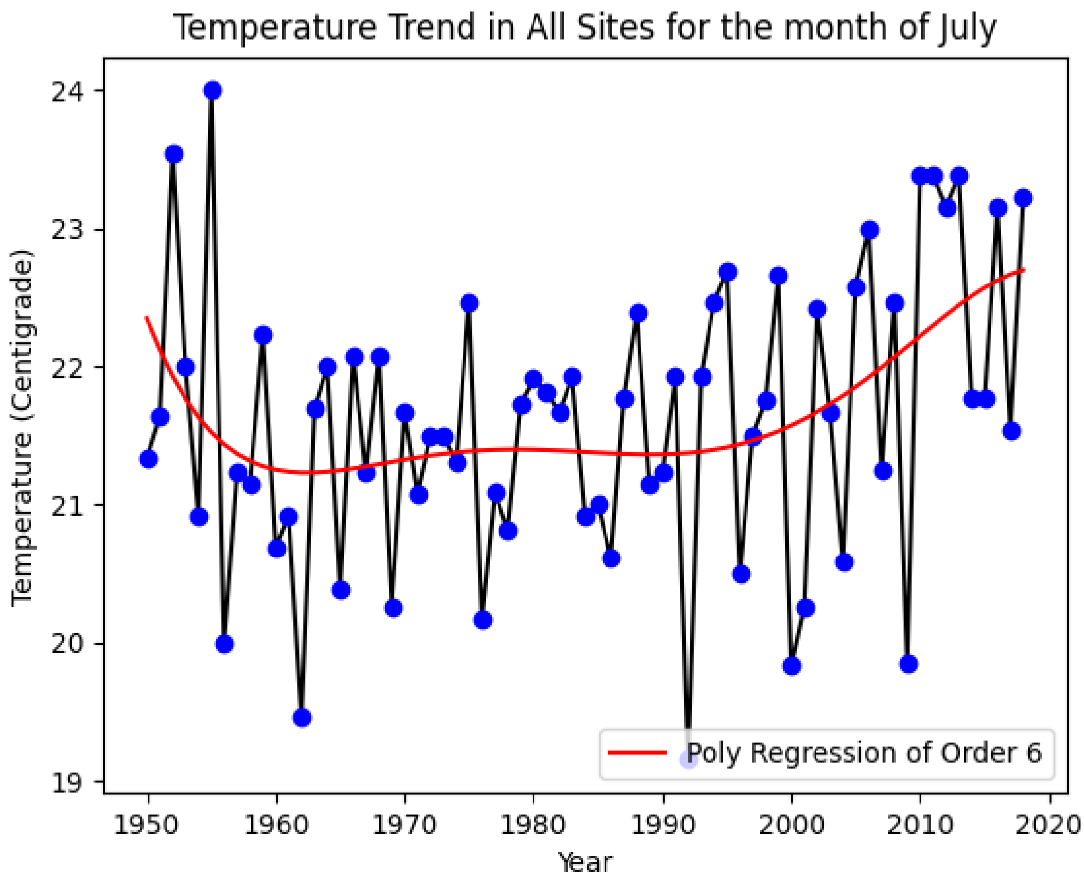

Figure 25: The change in mean temperature metric for the month of July for the average of all sites. The red line is the polynomial regression model run on the data to find any non-linear trends in temperature.

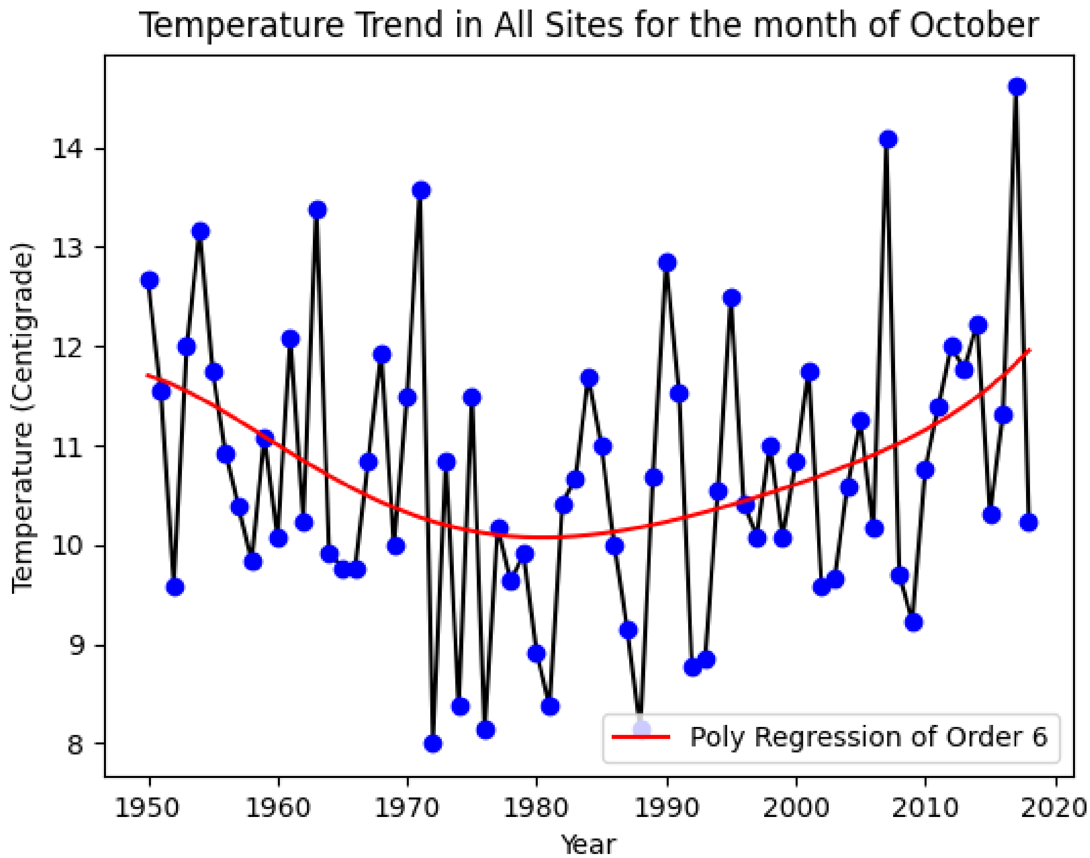

Figure 26: The change in mean temperature metric for the month of October for the average of all sites. The red line is the polynomial regression model run on the data to find any non-linear trends in temperature.

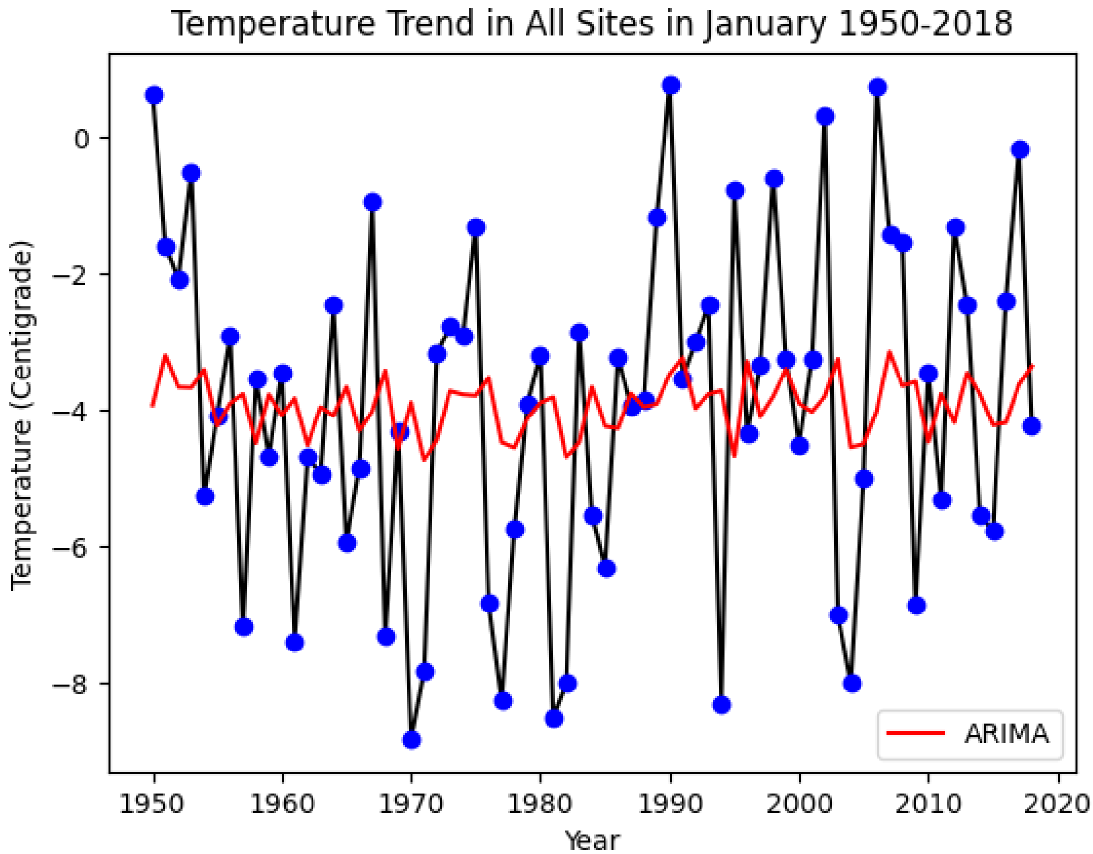

Figure 27: The change in mean temperature metric for the month of January for the average of all sites. The red line is the ARIMA model run on the data to find any trends in temperature that polynomial and linear models cannot identify.

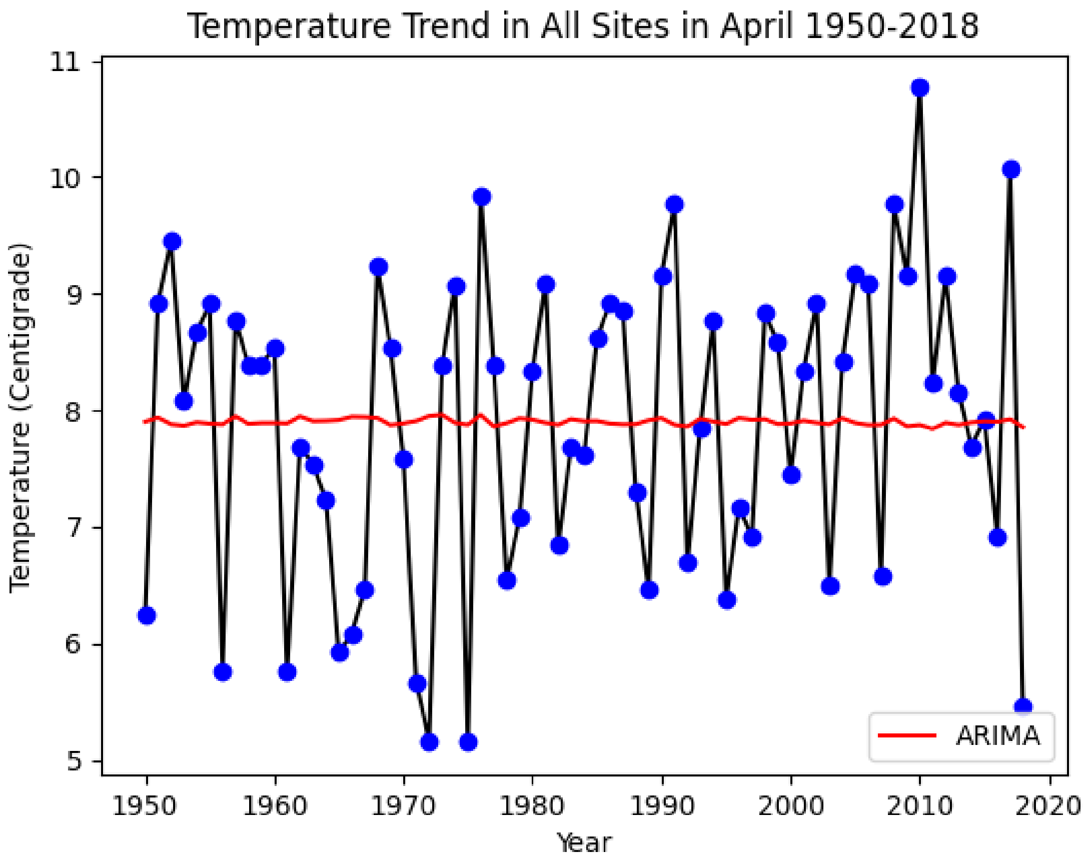

Figure 28: The change in mean temperature metric for the month of April for the average of all sites. The red line is the ARIMA model run on the data to find any trends in temperature that polynomial and linear models cannot identify.

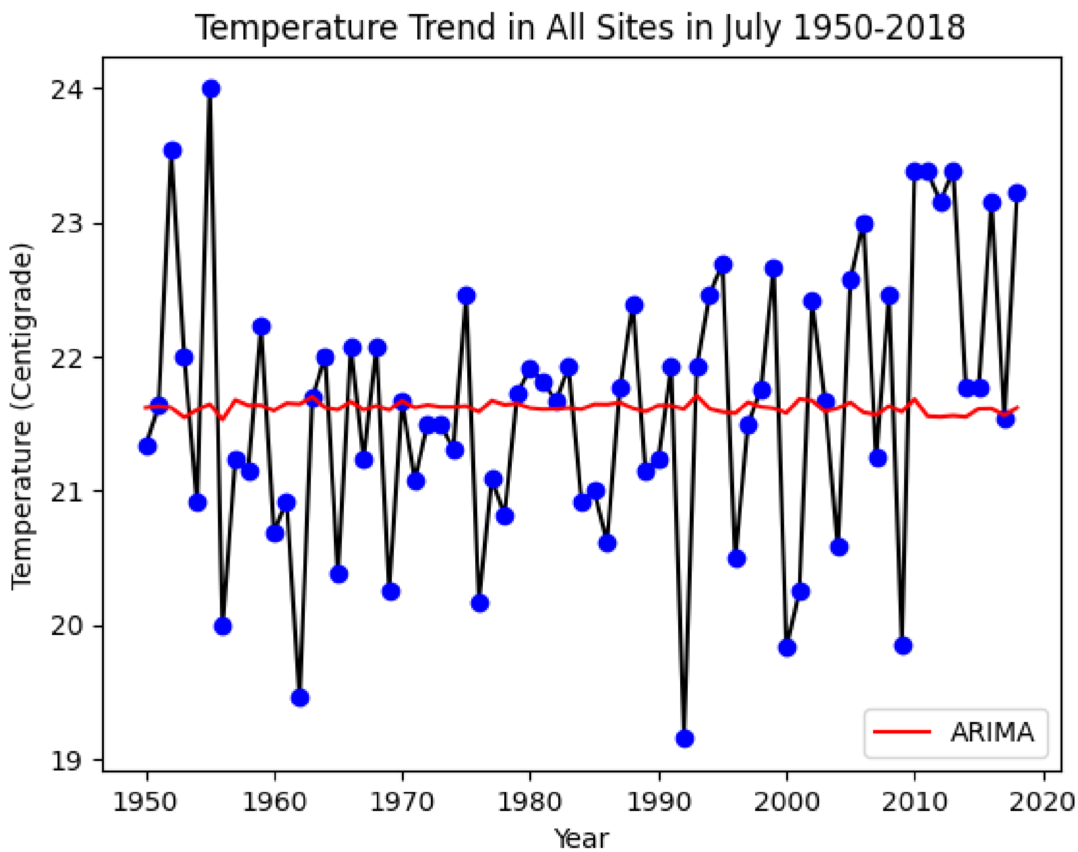

Figure 29: The change in mean temperature metric for the month of July for the average of all sites. The red line is the ARIMA model run on the data to find any trends in temperature that polynomial and linear models cannot identify.

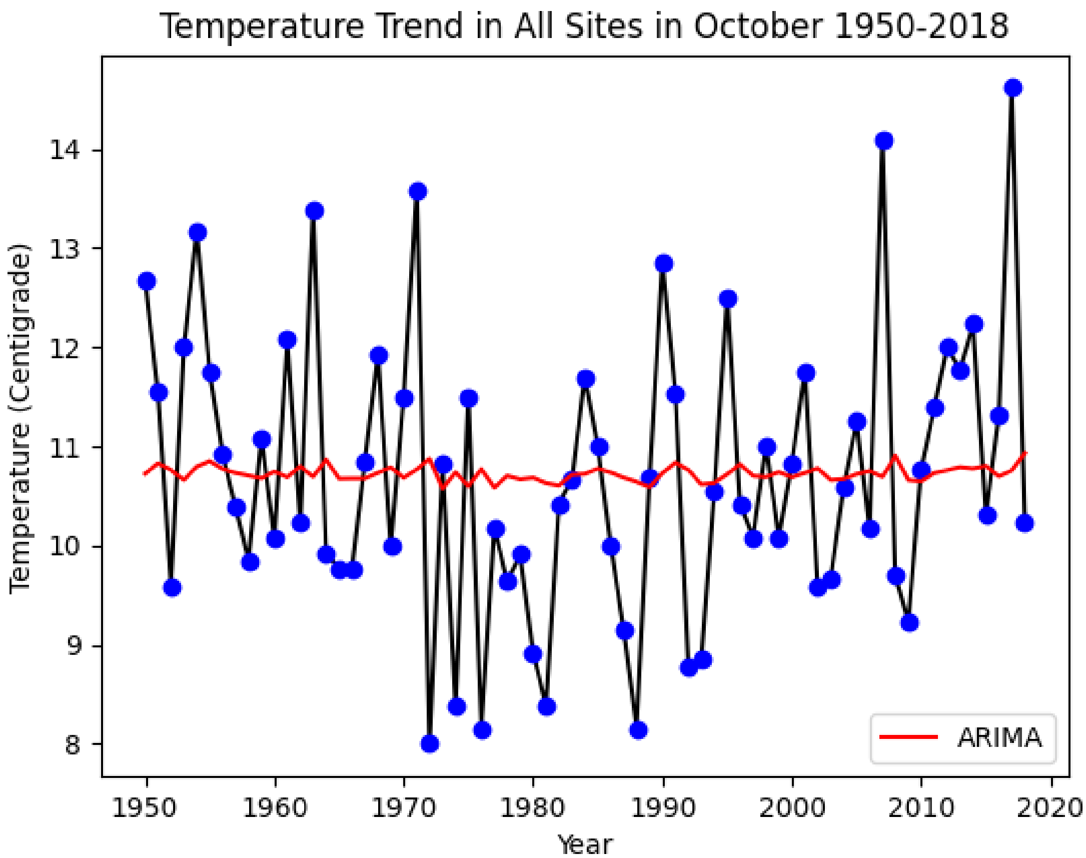

Figure 30: The change in mean temperature metric for the month of October for the average of all sites. The red line is the ARIMA model run on the data to find any trends in temperature that polynomial and linear models cannot identify.

Table 18: Linear regression testing metrics for all months. These metrics are from linear regressions run on the mean average across all sites. The columns represent the R^2 value of each linear model along with the p-val of the x-value coefficient (coefficient for years).

Month	R^2	P-Val
January	0.009	0.433
April	0.023	0.174
July	0.058	0.045
October	0.001	0.816

Table 19: Polynomial regression testing metrics for all months, the table shows the metrics used to measure the significance of the polynomial regression when ran on the mean average temperature metric for all sites. The significant coefficients (Sig Coeffs.) column represents the number of significant coefficients for each polynomial regression, since a 6th order polynomial was used, maximum number of significant coefficients is 6 (ignoring y-intercept).

Month	R^2	Sig. Coeffs.
January	0.171	1
April	0.173	1
July	0.178	2
October	0.152	1

Table 20: ARIMA model testing metrics for all months, the ARIMA models were run on all the mean average of all thirteen sites. The BIC value, Bayesian Information Criterion, is represented in the first column. The second column represents the number of coefficients which have a p-value less than 0.05 (maximum number of significant coefficients is 3).

Month	BIC	Sig. Coeffs.
January	331.68	2
April	243.23	2
July	210.99	2
October	255.47	2

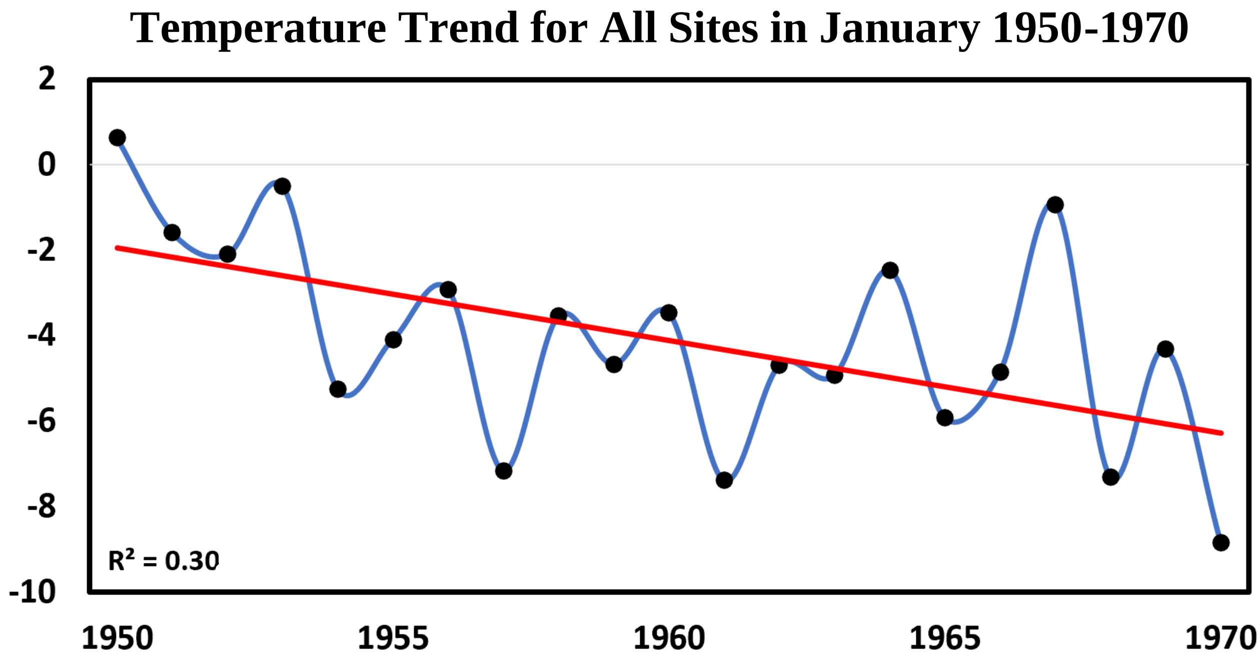

Figure 31: The change in mean temperature for the month of January for the average across all sitesfor th 1950-1970 subset of the data; the red line is the linear regression line. The graph also displays the R^2 value of the linear model.

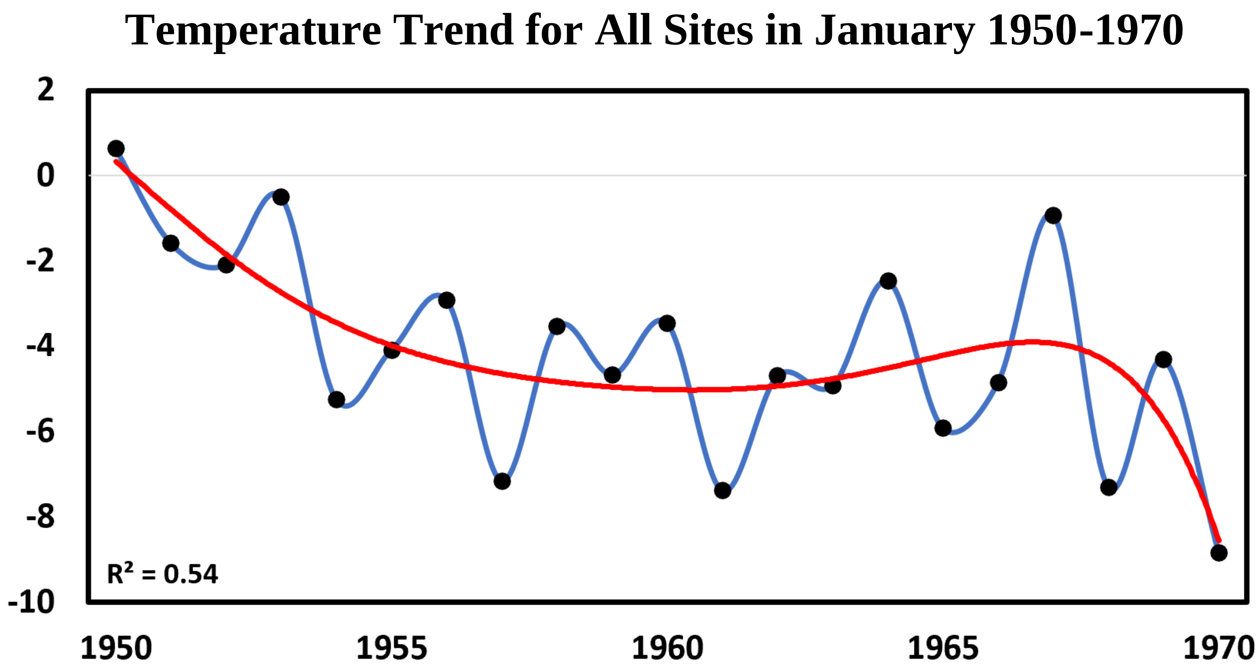

Figure 32: The change in mean temperature for the month of January for the average across all sites for the 1950-1970 subset of the data; the red line is the polynomial regression line. The graph also displays the R^2 value of the polynomial model.

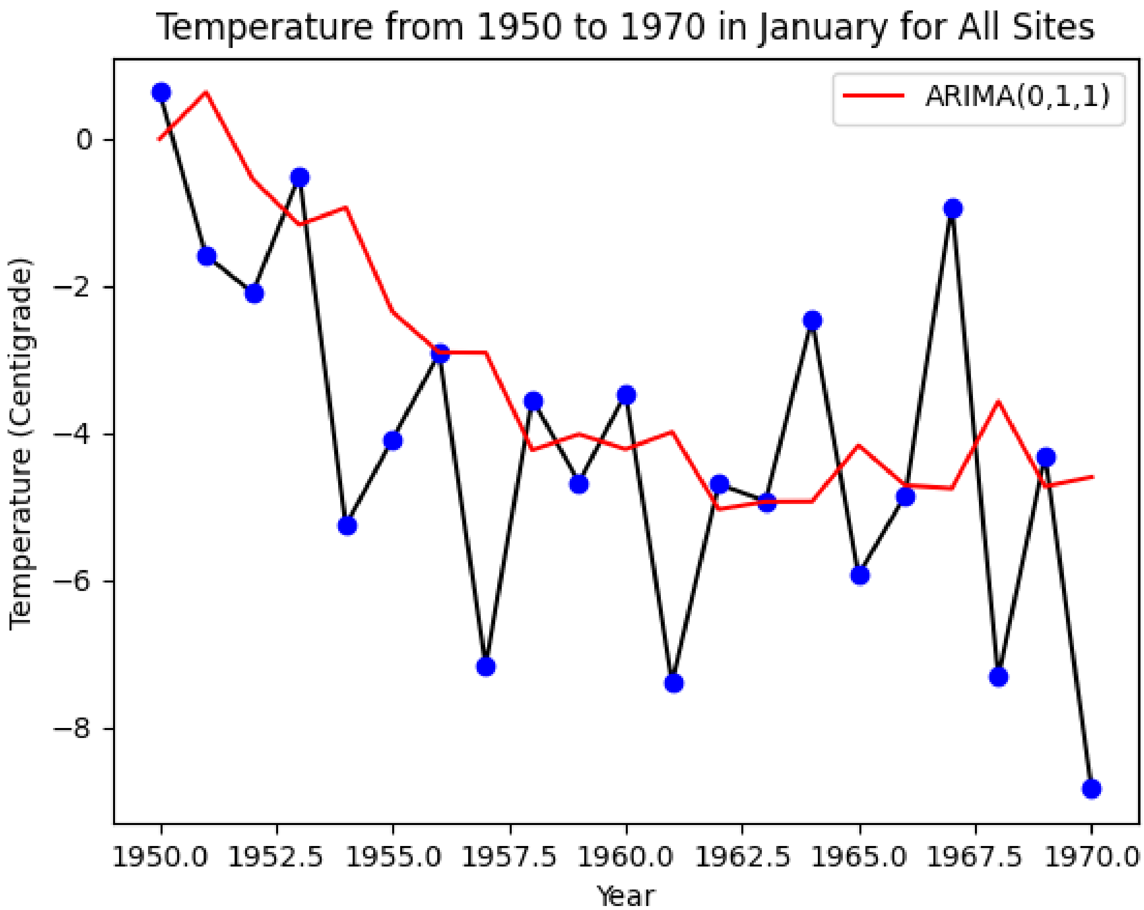

Figure 33: The change in mean temperature for the month of January for the average across all sites for the 1950-1970 subset of the data; the red line is the ARIMA model line. The (p,d,q) parameters are also identified in the upper right hand corner of the graph space.

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