Statistical Analysis of Meteorological Data to Investigate the Impact of Climate Change

1. Introduction

Climate change stands out as a primary challenge of our generation. In the news, we hear about glaciers melting, polar bears losing their habitat, and CO_2 levels rising. An ordinary person can not relate to those. Can we do a local analysis to find signs of climate change using data analysis in Python?

The National Oceanic and Atmospheric Administration has a website climate.gov which shows other signs of climate change such as Japanese Cherry Blossoms flowering earlier, increasing rate of receding glaciers, and the bleaching of coral reefs. The same site shares temperature data for the continent which shows that the average land and ocean temperature increased approximately 0.5°C for the last 20 years (NOAA Climate.org). It is hard for humans to comprehend this 0.5°C change over 20 years, because of the daily variation in temperature.

Further, this is not entirely accurate because climate change has a lot of variation from region to region. Certain areas might be more impacted by climate change than others. The goal of this paper was to explore meteorological data for the past 70 to 80 years to statistically demonstrate the impact of climate change in a handful of United States cities. In this paper, we looked at different ways to study meteorological data from different regions. We looked at plots of average temperature on a particular day over a century, modeled temperature over a year and compared it to historical data, and finally looked at extreme temperature events.

2. Methods

2.1 Study Systems

To find weather data for cities in the United States, we used the National Centers for Environmental Information (NCEI). The most consistent and reliable data in the NCEI's stations came from large airports and universities. These datasets contain information on wind, precipitation, daylight duration, snowfall, maximum and minimum temperatures, and other daily climate characteristics. Most of these had 25,000 recorded days.

The data in csv files were uploaded and analyzed by Pandas data frameworks. These data frames allowed quick manipulation of the data. Then, the individual data rows were removed if they contained null values. Also, rows containing multiple "9"'s in a row were considered invalid according to the NCEI's documentation and were removed accordingly.

For the analysis presented in this paper, the data used was from the John Glenn Columbus International Airport (1948 to 2022), Miami International Airport (1948 to 2022), Baltimore/Washington International Thurgood Marshall Airport (1939 to 2022), and Pittsburgh International Airport (1945 to 2022). The data contained columns that contained the date and minimum and maximum temperatures for each day. A new column was created that was the average of the minimum and maximum temperatures

2.2 Daily average temperature for a particular day over multiple years

This analysis is focused on studying data for one particular day over the entire recorded time for a city. The best-fit line and r-squared is determined using NumPy and plotted using Matplotlib.

2.3 Comparing historical average temperature fit to individual years

One can visualize average temperature over a year as an inverted parabola. To create a baseline for the first 30 years, we used the least squares method employing a 30-year time frame which provided a substantial dataset for statistical analysis. Goodness of fit to quadratic equation for the 30-years was calculated as r-squared using NumPy. Next, goodness of fit of data for subsequent individual years to the baseline equation were determined. The best fit line and corresponding r-squared is plotted for every single year. Significant deviation in temperature would show up as a lower r-squared value.

This goodness of fit was plotted as a function of the year using Matplotlib. Using this plot, a linear regression was performed on the r-squared.

2.4 Comparing number of statistically extreme daily high temperature events per year

The data was first grouped by the day of the year and a mean and standard deviation was calculated for each day. The following equation was used to calculate the standard deviation.

$$\sigma = \sqrt{\frac{\Sigma(x_i - \mu)^2}{N}}$$

Where σ is the standard deviation, x_i is a value, μ is the average value, and N is the number of values. For every year and every day, the number of occurrences where a day's high temperature exceeded 2 or 3 times the standard deviation for that day was counted. To calculate the occurrences the following equations were used.

$$Tobs > Tavg + 2\sigma$$

$$Tobs > Tavg + 3\sigma$$

Where T_{obs} is the observed temperature, T_{avg} is the average temperature for the day, and σ is the standard deviation for the day. Two graphs for each city were created for 2 sigma and 3 sigma excursions, respectively.

3. Results and Discussion

3.1 Daily average temperature for a particular day over multiple years

Fig. 1. John Glenn Columbus International Airport shows an upward trend of the average temperature on January 1st but the r-squared value is very low (0.0375). Despite observing a 0.48°C/10 year temperature increase, this temperature increase is not statistically significant.

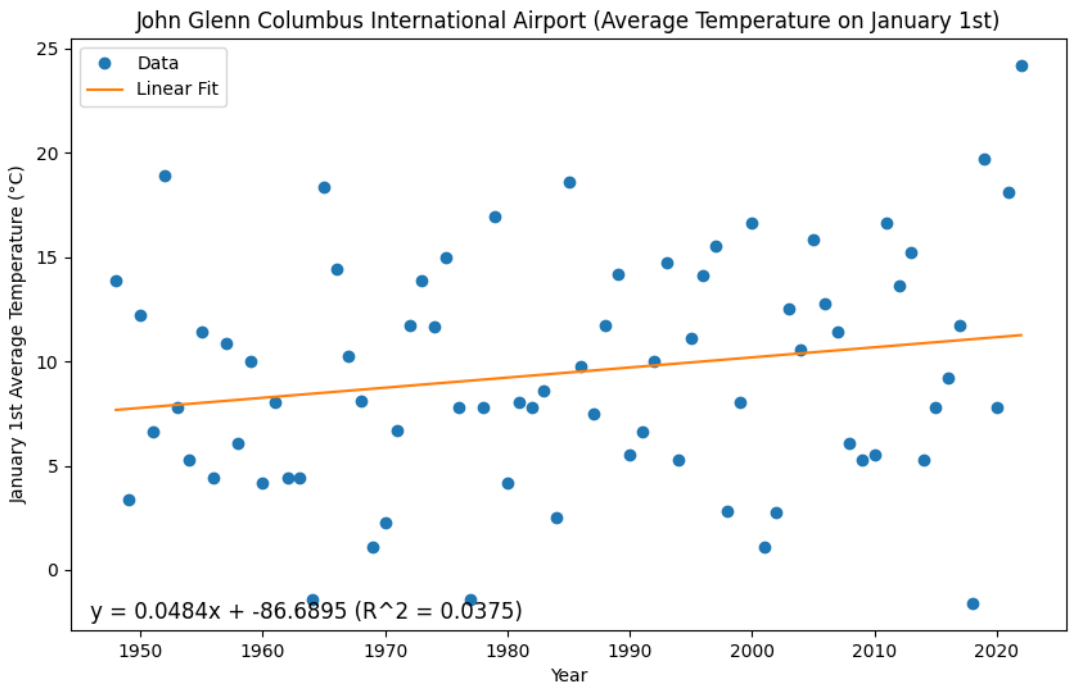


Fig. 2. Miami International Airport shows an upward trend of the average temperature on January 1st but the r-squared value is 0.1385.

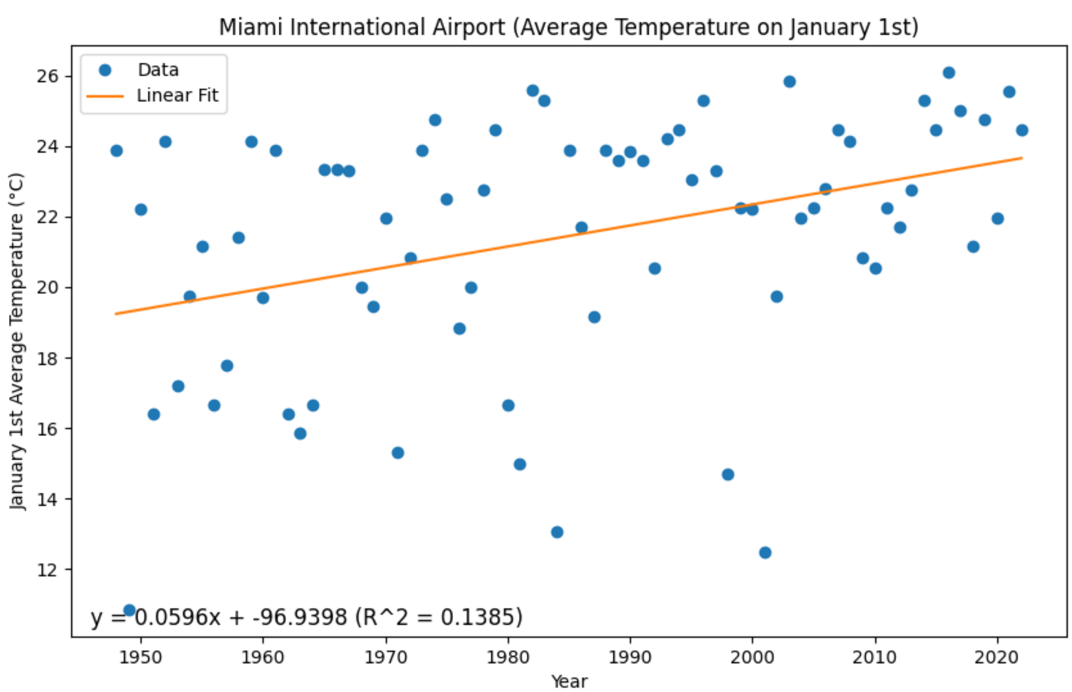
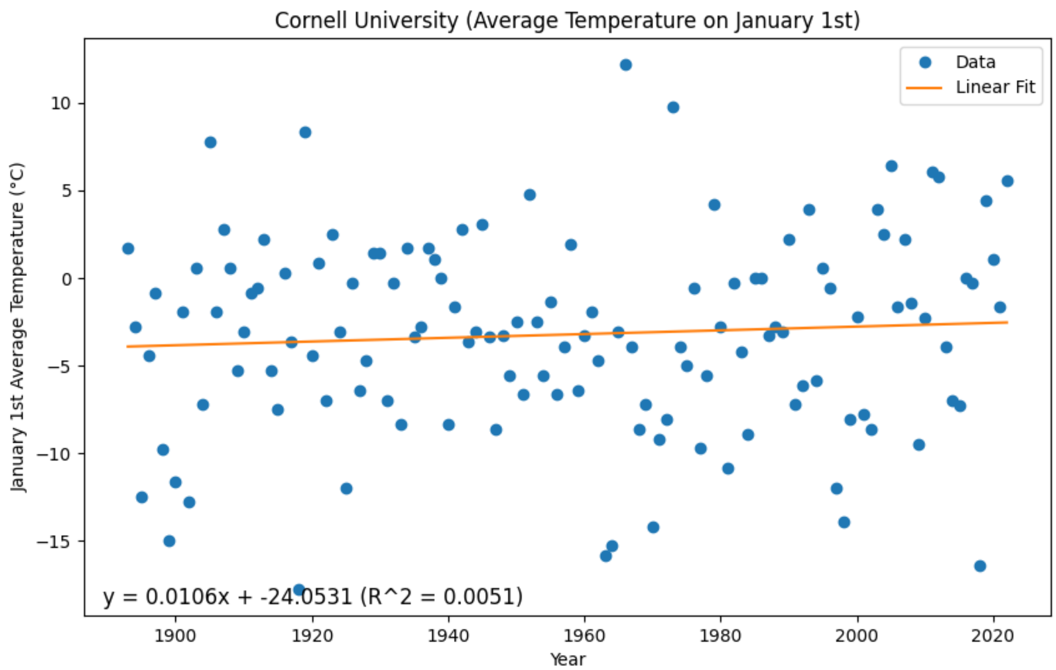


Fig. 3. Cornell University shows an upward trend of the average temperature on January 1st but the r-squared value is 0.0051.



In all three cases, the temperature rise per year is increasing on January 1st, but the r-squared value of the graph is quite low and visually most of the data points do not fall on the line. A common person would not observe this increase without the fit because there is a large variation. This is not conclusive evidence that climate change is occurring.

3.2 Comparing historical average temperature fit to individual years

Fig. 4. John Glenn Columbus International Airport daily average temperature in 1948 with quadratic least square fit from the first 30 years. Shows an r-squared value of 0.7767 which is a

decent fit for the data. In other words, the quadratic fit fits the data quite well.

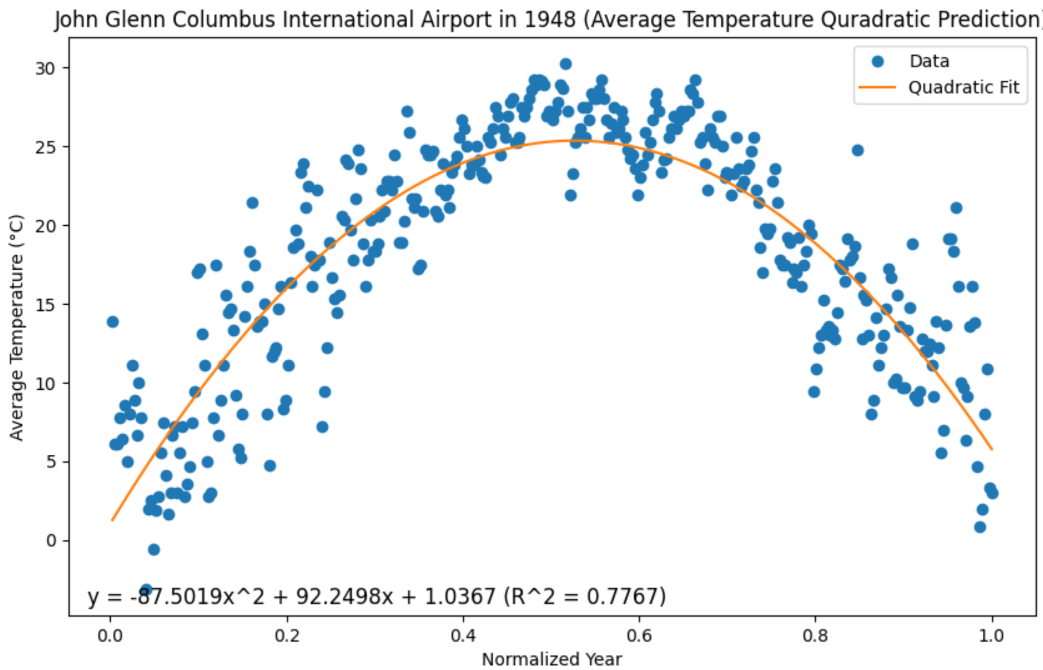


Fig. 5. John Glenn Columbus International Airport daily average temperature in 2020 with quadratic least square fit from the first 30 years. Shows an r-squared value of 0.6082 which is a more inaccurate fit for the data. The quadratic fit doesn't fit well and there are a lot of points higher than the predicted curve.

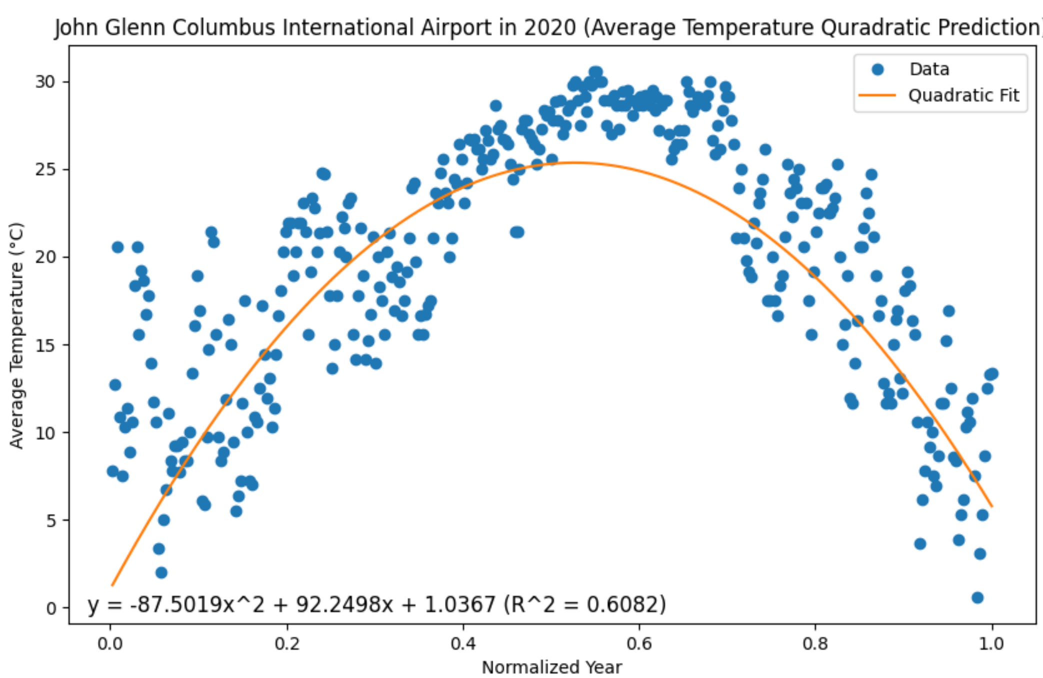


Fig. 6. John Glenn Columbus International Airport shows a negligible decrease in r-squared from the predicted average temperature for the first 30 years. The r-squared value is still low.

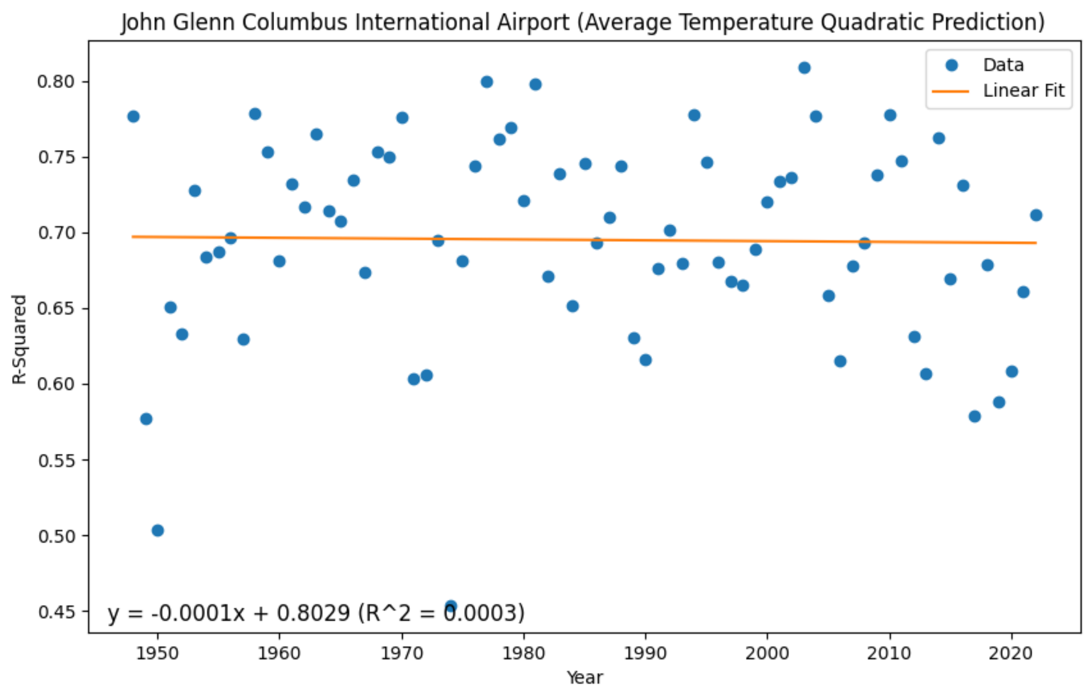
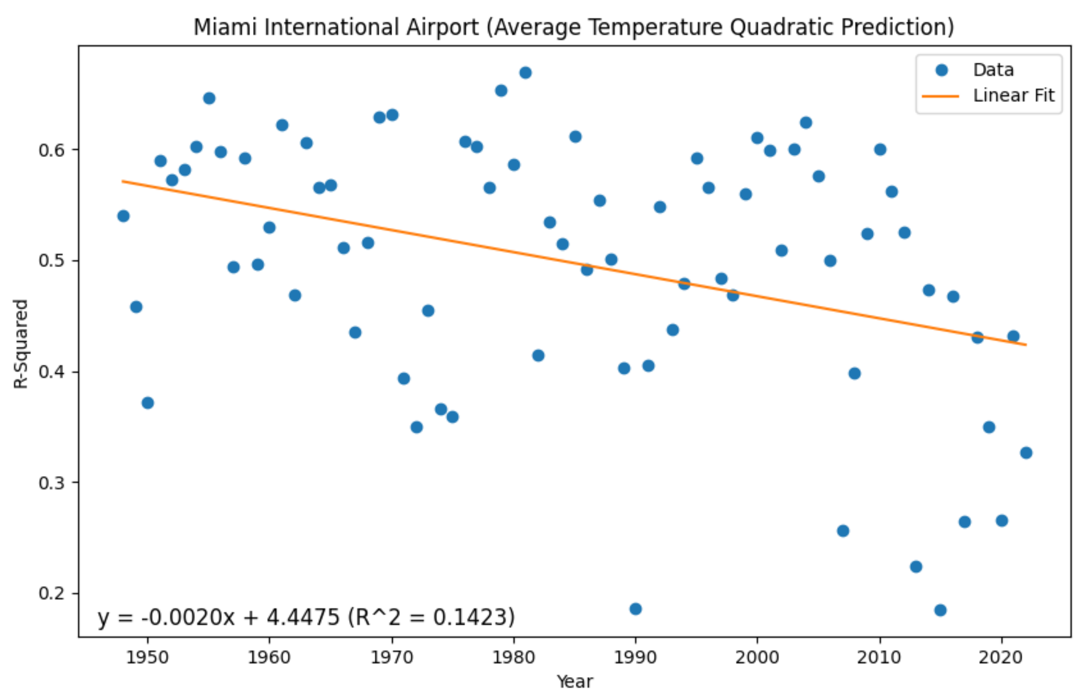


Fig. 7. Miami International Airport shows a steep decrease in r-squared from the predicted average temperature for the first 30 years. The r-squared value is still low.



When the r-squared value decreases, it means that the variability between the predicted and actual values is becoming greater. For both Columbus and Miami, there is a negative trend in the r-squared value over the years. However, in both cases the r-squared value of the graph is quite low as visually most of the data points do not fall on the line. This is not conclusive evidence that climate change is occurring.

3.3 Comparing number of statistically extreme daily high temperature events per year

Fig. 8. John Glenn Columbus International Airport shows a positive trend in the frequency of high temperature excursions that are more than 2 standard deviations away from the average.

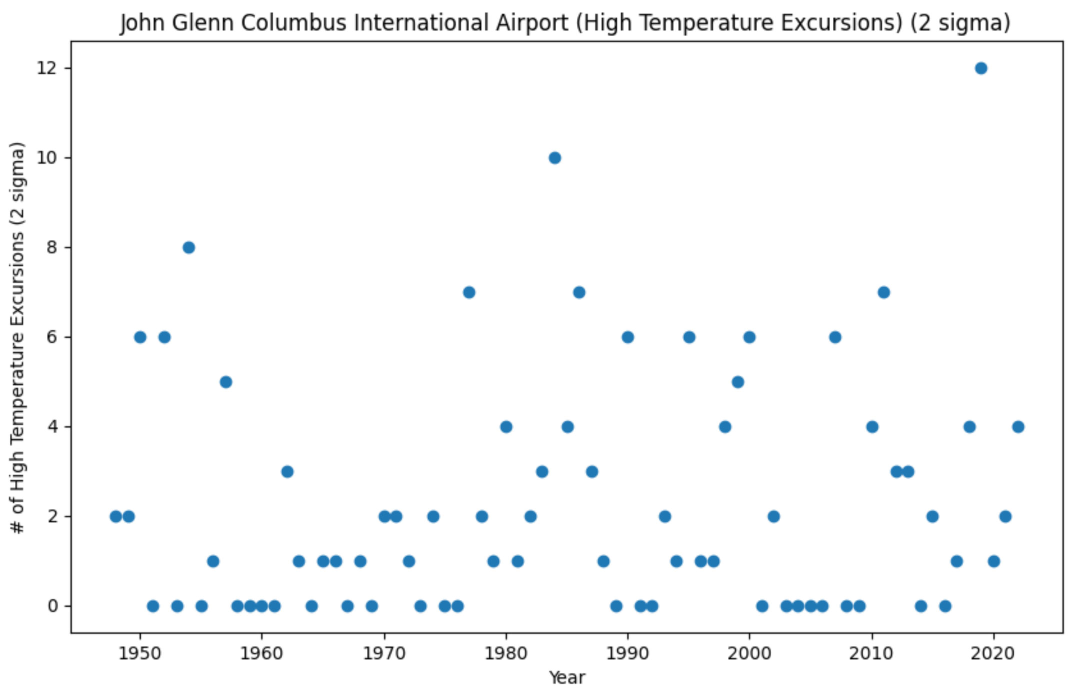


Fig. 9. John Glenn Columbus International Airport shows a positive trend in the frequency of high temperature excursions that are more than 3 standard deviations away from the average.

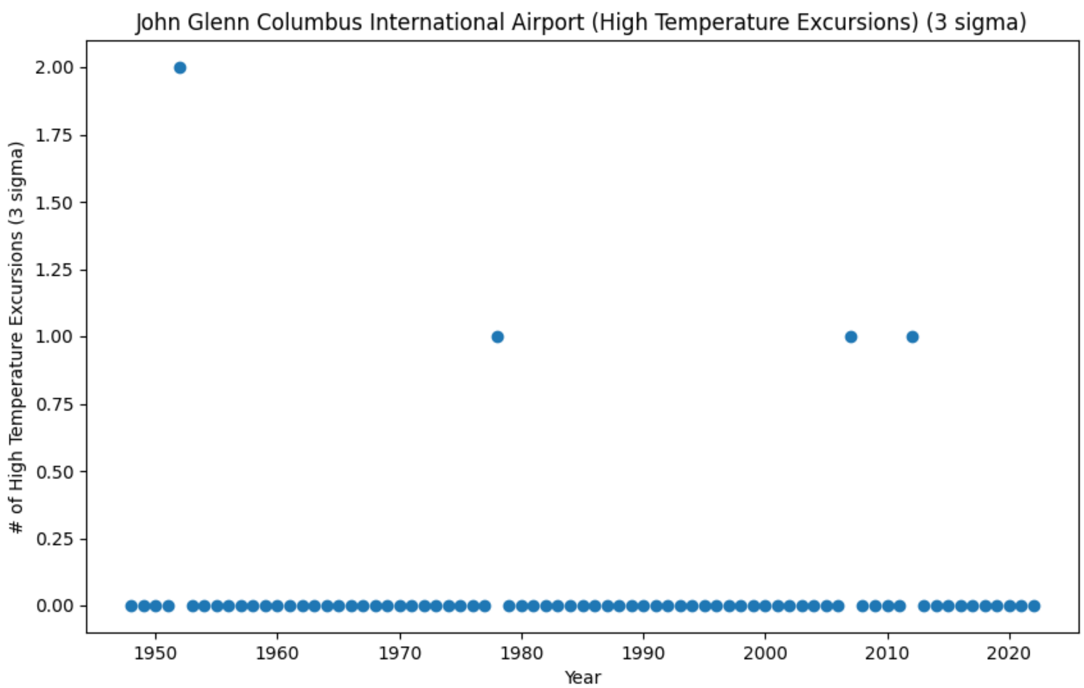


Fig. 7. Miami International Airport shows a positive trend in the frequency of high temperature excursions that are more than 2 standard deviations away from the average.

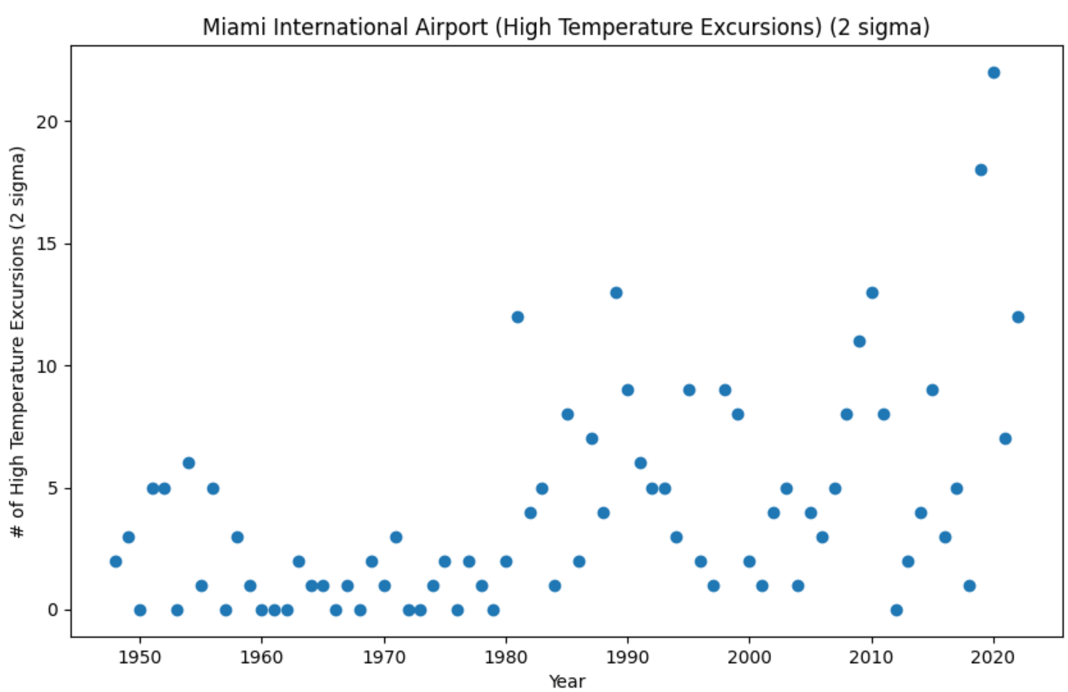


Fig. 10. Miami International Airport shows a positive trend in the frequency of high temperature excursions that are more than 3 standard deviations away from the average.

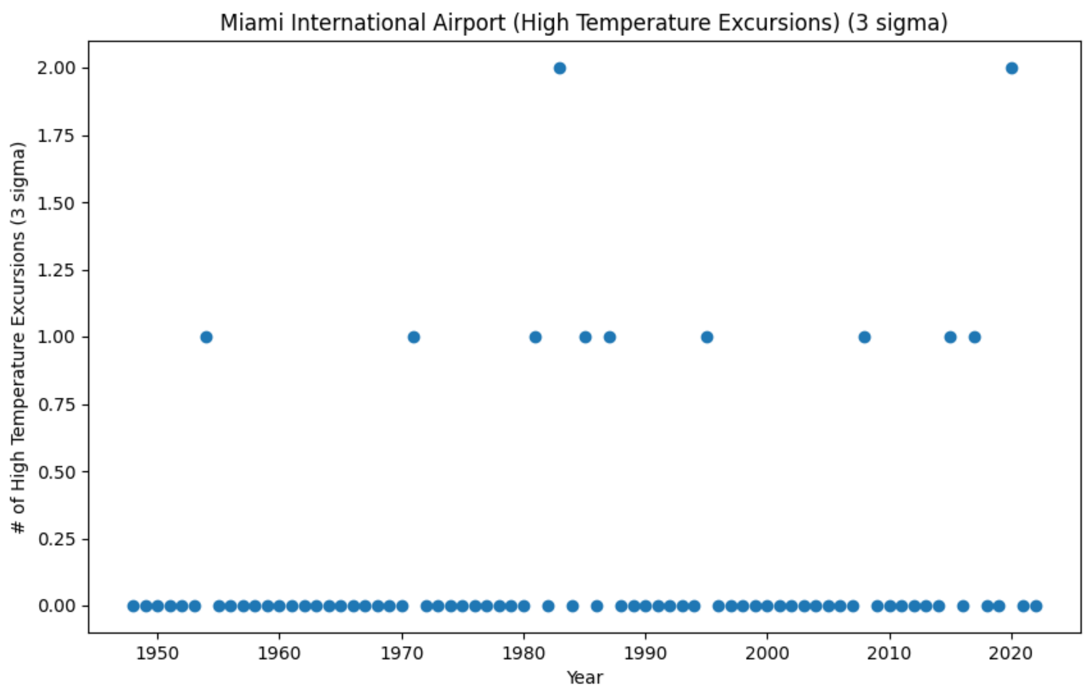


Fig. 11. Cornell University shows no correlation in the frequency of high temperature excursions that are more than 2 standard deviations away from the average.

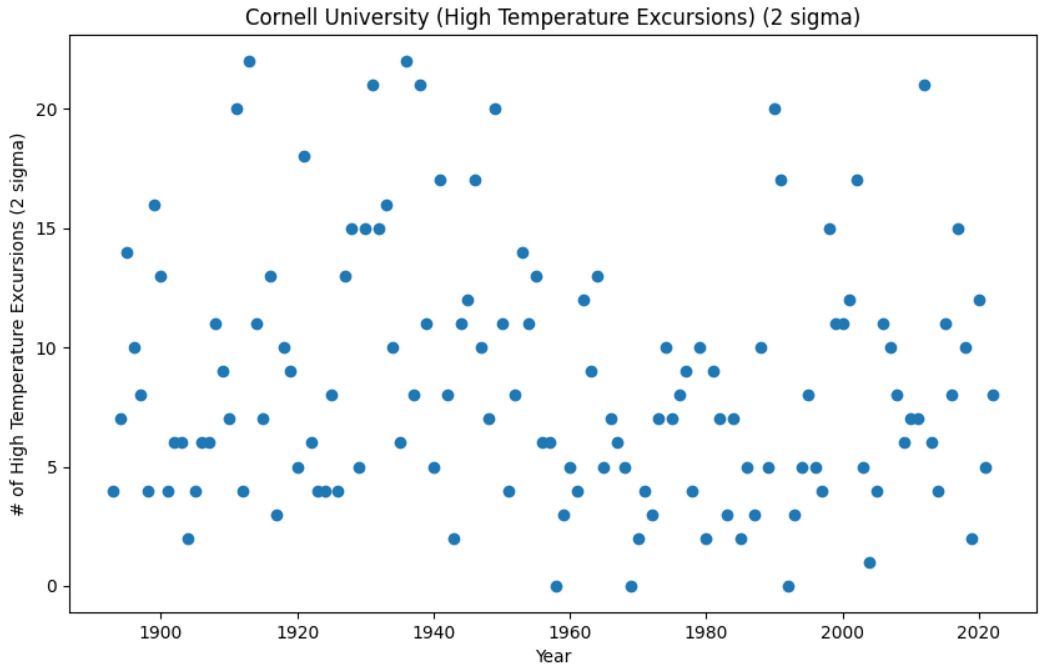


Fig. 12. Cornell University shows no correlation in the frequency of high temperature excursions that are more than 3 standard deviations away from the average.

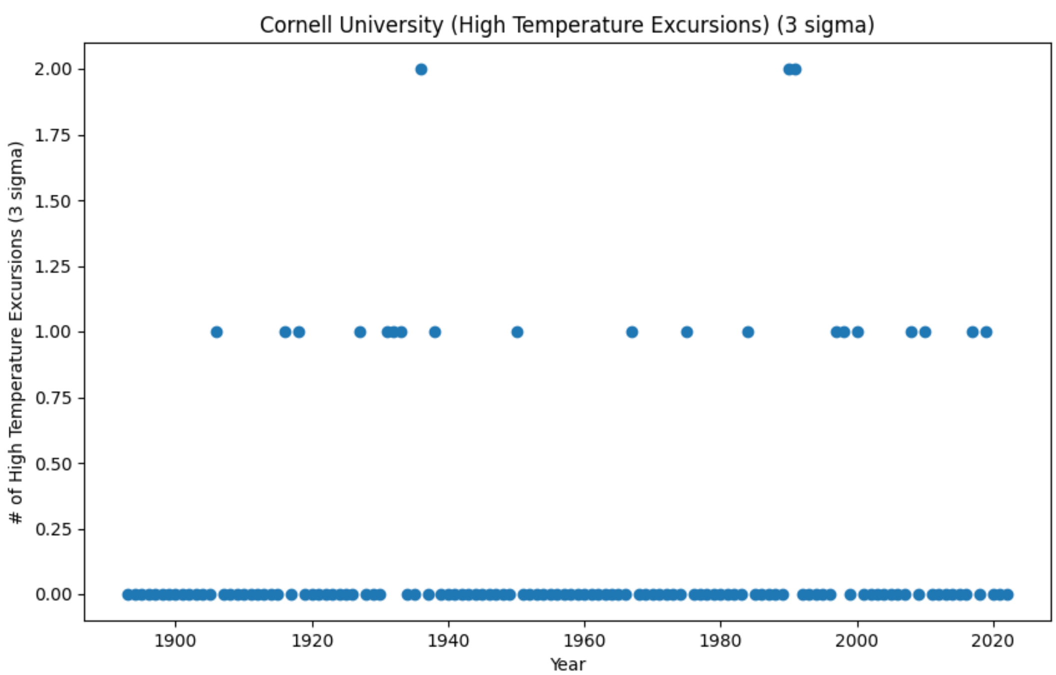


Fig. 13. Baltimore/Washington International Thurgood Marshall Airport shows a positive trend in the frequency of high temperature excursions that are more than 2 standard deviations away from the average.

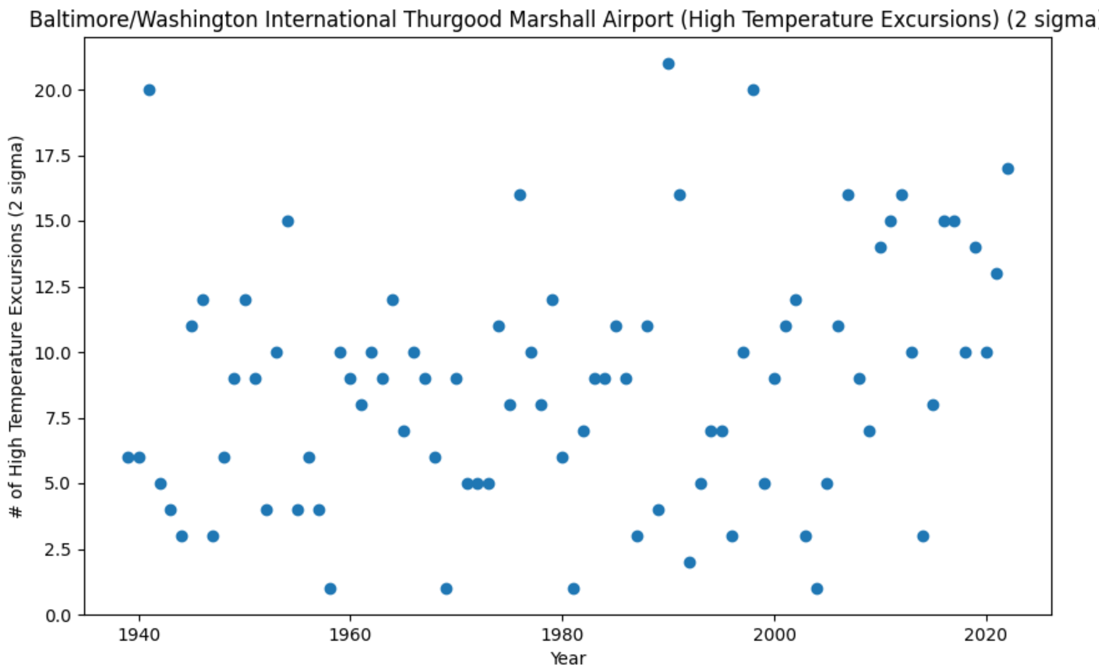
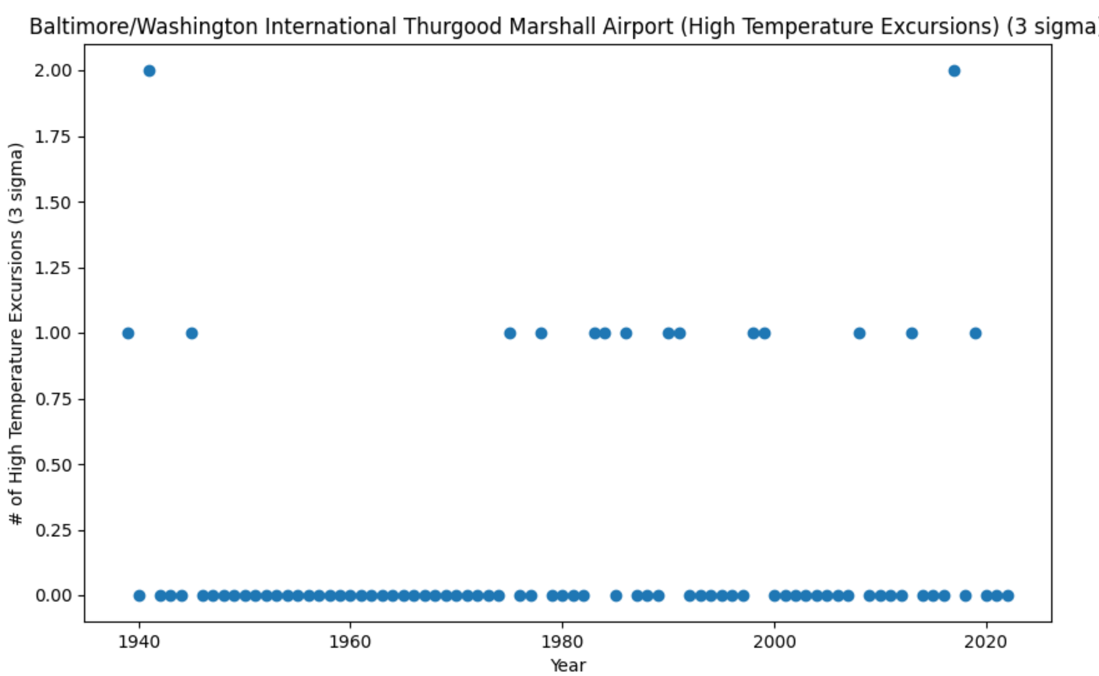


Fig. 14. Baltimore/Washington International Thurgood Marshall Airport shows a positive trend in the frequency of high temperature excursions that are more than 3 standard deviations away from the average.



Although the data varied from city to city, the data for Columbus, Miami, and Baltimore show a positive trend in the frequency of these temperature excursions. However, some cities such as Cornell show less shifts than others. The average temperature is becoming more variable and shows the impact of climate change. This variability is a good indicator of climate change (Katz and Brown).

4. Conclusion

Climate change is a complex topic. Despite all the data collected by scientists from ocean heat to species growing earlier, an average person has a difficult time grasping climate change. It is not easy to conclude that climate change is impacting us because there is too much variation from day to day. Looking at a single day every year yields a low r-squared, and is not conclusive of climate change Though creating a regression for the year shows a better r-squared, it is not enough to make a conclusion. The extreme events visually and statistically show that the number of extreme events show more consistent data. These extreme events show variability and sensitivity which is even more important than increases in average temperature (Katz and Brown). Some cities will experience more significant changes than others as seen in the graphs.

This variation might be because of a city's proximity to water and the equator, population, or even topography. This definitely requires more research.

5. References

NOAA Climate.gov. (2021). *Global Temperature Anomalies - Graphing Tool*. https://www.climate.gov/maps-data/dataset/global-temperature-anomalies-graphing-tool

Katz, R. W., & Brown, B. G. (1992). Extreme events in a changing climate: Variability is more important than averages. *Climatic Change*, *21*(3), 289–302. https://doi.org/10.1007/bf00139728