Exploratory analysis of Los Angeles meteorological data

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## **Introduction**

The scientific consensus surrounding the question of climate change is that it is not only occurring, but it is a result of human activity. The 2018 IPCC Special Report on the impacts of global warming claims that anthropogenic climate change has resulted in an increase in global temperatures by approximately 1.0°C above pre-industrial levels and expects that this figure will jump to 1.5°C between 2030 and 2052. They point out the consequences of anthropogenic climate change have included but are not limited to rising global temperatures, rising sea levels, and an increased frequency in natural disasters such as droughts, floods, and storms. The report claims that the risk of these consequences is significantly higher if global warming reaches 2°C than if it is limited to 1.5°C, and the IPCC stresses that the world needs to act now if we are going to succeed in keeping temperature rise to below 1.5°C (IPCC).

There are some places on Earth that are most susceptible to climate change consequences than others. One of these places is Los Angeles, California. In recent years, Los Angeles county, as well as a large share of California, has been experiencing an ongoing drought. The longest duration of drought began in December 2011 and persisted until March 29, however 29% of California is still in drought. (drought.gov) Additionally, being located on the pacific coast sets Los Angeles up to be one of the places most affected by sea level rise. The Los Angeles area is expected to match global sea level rise estimates of 0.1 - 0.6 m from 2000 to 2050 and 0.4 - 1.7 m from 2000 to 2100, with financial losses from building stock ranging from 410 million to 714 million US dollars (Griffman et al).

Because of the high risk climate change poses to Los Angeles and its nearly 19 million residents, it is vitally important for Los Angeles to look into mitigation techniques. However, before these techniques can be accurately developed, it is essential to understand the trends of local climate variables over the past several decades to help predict how they will behave in the future. Using meteorological data from Los Angeles Airport, this study explores the trends of temperature, relative humidity, and depth of liquid precipitation from 1972 to 2019 to extrapolate how these variables will behave in the future.

## **Methods**

This study utilizes bivariate analysis to estimate trends of Los Angeles’ temperature, relative humidity, and total liquid precipitation with respect to time. The dataset used in this study to analyze the aforementioned trends was pulled from [NOAA](ftp://ftp.ncdc.noaa.gov/pub/data/noaa/isd-lite/) and represents hourly meteorological data for Los Angeles International Airport from 1973 to 2019. All data analysis was performed using R Version 3.6.0 and formatted in rstudio.cloud. After removing erroneous and incomplete data from the original dataset, I used **dplyr** to mutate the dataset, which was originally expressed as hourly data, to create year, month, and combined year and month date objects using **lubridate** and averaged the data of each meteorological variable by each of these date objects. Each summarized variable was then plotted against a time variable using **ggplot2**. The read.me file which accompanies the original dataset noted that a large number of the precipitation measurements were missing, but in looking at the data I noticed that these data were in fact still there, so I decided to ignore this message.

### Residual Analysis

Each plot showing a meteorological variable over time is accompanied with a residual dependency plot, a normal quantile-quantile plot, and a spread-location plot of the relevant data. The residual dependency plot is used to evaluate how well the fit assigned to the meteorological variable’s relationship to time. A loess fit was used for the residual dependency plot, as it will account for shifts in trends throughout the data rather than the overall trend of the data. If this fit is flat, the fit assigned to the fitted values is appropriate. The quantile-quantile plot is used to show how normalized the spread of residuals is. The residuals will be normally distributed if the sample distribution equals the theoretical distribution, meaning that the residuals line up perfectly along x=y. The spread-location plot shows whether the variability in the data changes with increasing fitted value.

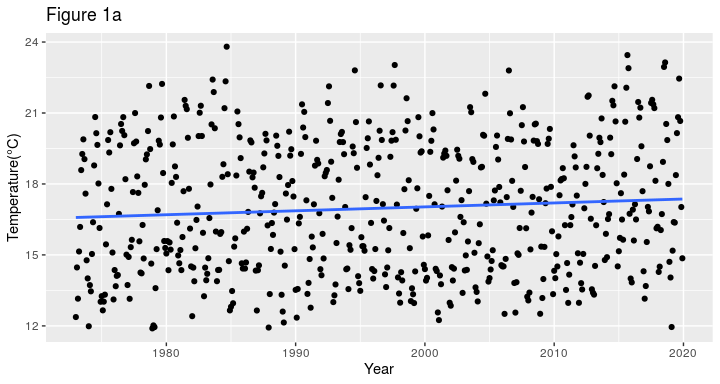
### Data Normalization

As this study is simply exploratory in nature and does not employ any hypothesis tests, I opted not to reexpress the data to normalize residuals. I wanted to represent the data as it is was originally measured, as I wanted the trends of the data to be as visually clear as possible. The appropriate transformations needed to normalize data for hypothesis testing is outlined for each figure in the results section.

## **Results**

The data analysis yielded that over the 48-year span of data collection, the average temperature increased by 0.0166°C per year, the relative humidity decreased by 0.0653% every year, and total precipitation decreased exponentially at a rate of 0.08214x^2 - 0.03236x.

### Average Monthly Temperature



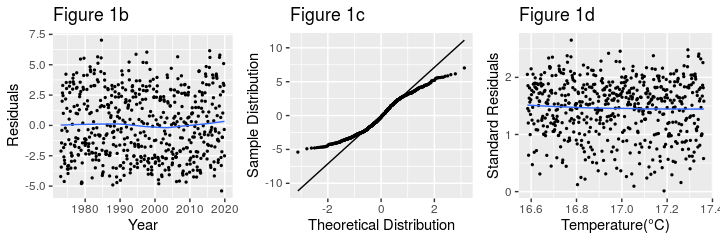
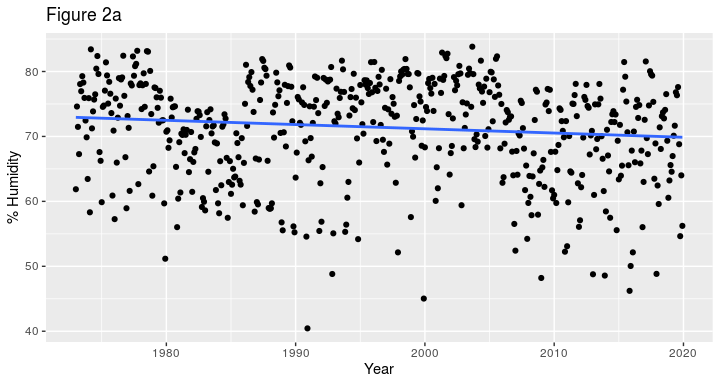


Figure 1. Average temperature (°C) as a function of time (months).

The trend of average temperature per year, as shown in figure 1a, is represented with a robust regression and described by the equation y = 0.0166x - 16.17, meaning over the 47 year span of the data, the average temperature in Los Angeles has risen 0.7802°C. Figure 1b is a residual dependency plot for the temperature data that shows a relatively flat loess fit, showing the residuals of figure 1a to be distributed relatively evenly across a linear fit, meaning a parametric fit of order 1 is appropriate for this data. Figure 1c is a normal quantile-quantile plot of the temperature data which shows the residuals of figure 1a to not follow a normal distribution, as the first and fourth quartile of the data deviate upward and downward respectively, compared to the normal distribution shown by the trendline. This data would need to be transformed through raising the y (avg.temp) variable to the 3rd power to normalize the distribution of the residuals. Figure 1d is a spread location plot, which shows a flat loess fit, meaning there is very little change in variability as a product of location.

### Average Monthly Humidity



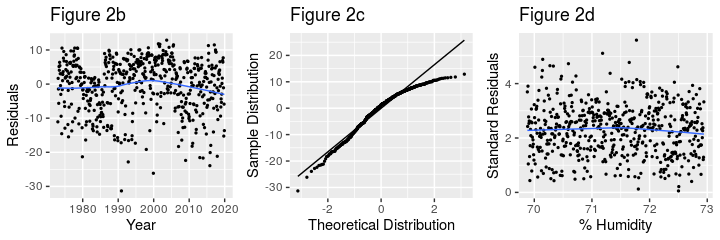
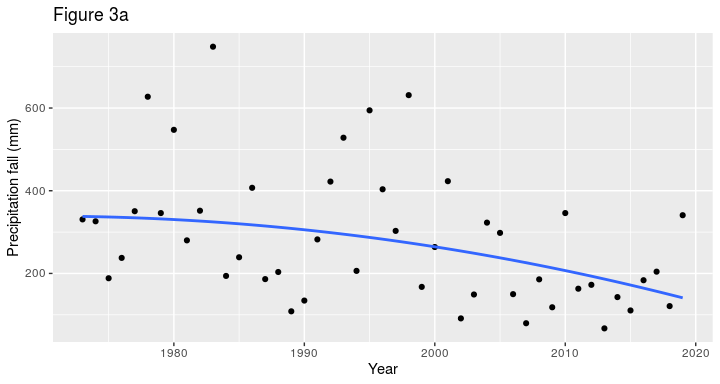


Figure 2. Average relative humidity (%) as a function of time (months).

The trend of average relative humidity per year, as shown in figure 2a, is represented with a robust regression and described by the equation y = -0.0653x + 201.7, meaning over the 47-year span of the data, the average relative humidity in Los Angeles has dropped 3.069%. Figure 2b is a residual dependency plot for the humidity data that shows a relatively flat loess fit, showing the residuals of figure 2a to be distributed relatively evenly across a linear fit, meaning a parametric fit of order 1 is appropriate for this data. Figure 2c is a normal quantile-quantile plot of the humidity data which shows the residuals of figure 2a to not follow a normal distribution, as the fourth quartile of the data deviates downward with respect to the normal distribution shown by the trendline. This data would need to be transformed through raising the y (avg.rf) variable to the 2nd power to normalize the distribution of the residuals. Figure 2d is a spread location plot, which shows a relatively flat loess fit, meaning there is very little change in variability as a product of location. There appears to be an abnormality in the data from 1980 to 1986, and again from 2007 to 2015, where there are very few months with an average humidity of 75% or greater. The raw data does show many hourly measurements of above 75% within this span, so this abnormality is likely not due to holes in the data. Perhaps there was a natural phenomenon during this period which made the climate of Los Angeles relatively drier than usual, or large-scale meterological patterns associated with periods of draught. This is something that could be investigated with further research.

### Total Yearly Rainfall



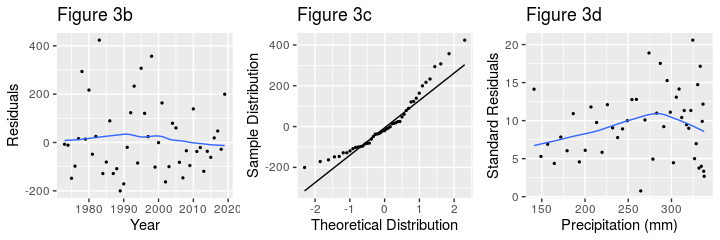


Figure 3. Average liquid precipitation depth (mm) as a function of time (years).

The trend of total rainfall per year, as shown in figure 3a, is represented with a robust regression and described by the equation y = -0.08214x^2 + 0.03236x - 3.184, meaning over the 47 year span of the data, the total yearly rainfall in Los Angeles has dropped 179.9mm. Figure 3b is a residual dependency plot for the precipitation data that shows a relatively flat loess fit, showing the residuals of figure 3a to be distributed relatively evenly across a parabolic fit, meaning a parametric fit of order 2 is appropriate for this data. Figure 3c is a quantile-quantile plot of the precipitation data which shows the residuals of figure 3a to not follow a normal distribution, as the first and first and fourth quartiles of the data both deviate upward with respect to the normal distribution shown by the trendline. This data would need to be transformed through taking using the log of the y (total.rf) variable to normalize the distribution of the residuals. Figure 3d is a spread location plot, which shows an upward loess fit, meaning as precipitation increases, the location of the residuals increases until around 275 mm, then decreases. However, this fit should become flatter when the rediduals are normalized as stated above. Because the data yielded many months with little to no rainfall, I decided to represent this data per year rather than month, as it gave a clearer picture of the trend of rainfall.

## **Discussion**

The analysis of this data is in agreenment with the general scientific consensus that average yearly global temperatures are rising. According to [climate.gov](https://www.climate.gov/news-features/understanding-climate/climate-change-global-temperature), the average global increase in temperature has been 0.18°C per decade, which is not far off from the rate of 0.166°C per decade calculated in this study (percent difference = 8.1%). This would suggest that Los Angeles is warming relatively slightly slower than the rest of the world. An explanation for this could be that Los Angeles was already a relatively hot location, so it won’t have as larger of a temperature change compared to locations at higher latitudes. Because the temperature rise rate from this study is so similar to the global temperature rise, I expect Los Angeles to hit the 1.5°C within the span given in the IPCC report. Ideally, this study would have estimated reaching this threshold based off of preindustrial temperature averages in Los Angeles, but I could not find reliable temperature data for that long ago.

Additionally, the data yielded an exponential decrease in total yearly precipitation volume. I was unexpecting to find this to be the case, especially considering the decrease in recent drought as shown by [drought.gov](https://www.drought.gov/drought/states/california). This significant decrease in rainfall signifies an increased risk for further drought in the future. The sustained decrease in humidity also shows Los Angeles to becoming a drier climate, another contributor to increased droughts.

A decrease in temperature also shows potential contribution to California’s drought. There have been studies that link rising temperatures to increased melting of snowcapped mountains in the Sierra Nevada mountain range, which provides 60% of California’s drinking water. Because snow is melting faster, it delivers more meltwater than the landscape can handle at once, so much of this water is lost. For the rest of the summer, there is no consistent meltwater flow, which results in drought (Barnett et al). In this way, the increase in temperature seen in Los Angeles could be contributing to California’s drought. However, to confirm this, temperature data from the mountain range would need to be collected and compared to the data from this study to ensure the range is facing the same temperature increase as Los Angeles. Additionally, the increase in temperature shown in this study does suggest a response in sea level rise, but an appropriate next step in this research would be to analyze sea level rise data and compare it with temperature rise trends to see if there is a cause and effect relationship that can be gleaned.

## **Conclusion**

Ultimately, this study shows that given the risk of climate change consequences, it is imperative that Los Angeles invest in climate change mitigation strategies. The increases in temperature and the decreases in humidity and precipitation show that Los Angeles is trending towards a warmer, drier climate. This data does not show a direct linkage to anthropogenic climate change, but further research utilizing trends in variables such as carbon emissions and deforestation may yield cause and effect relationships with the trends analyzed in this study. Luckily for Los Angeles, California is one of the most forward thinking and innovative states when it comes to climate action, so as long as climate variables such as those in this study are measured, monitored, and projected, we can keep a close watch on the way in which our climate is changing.

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