2022 Effects of wildfires and other pollutants on solar energy production

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Abstract

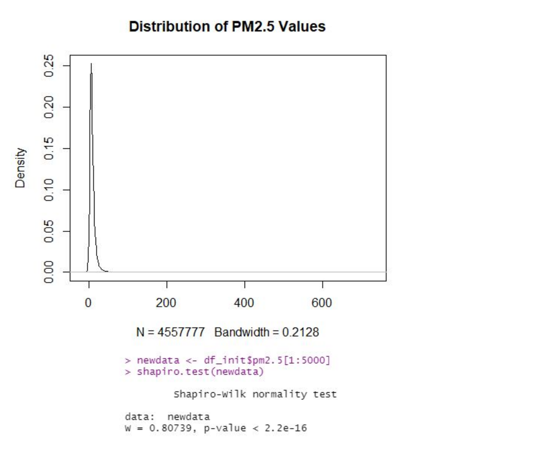
Although the world still relies on fossil fuel combustion for most energy production, renewable energy methods have become more prevalent. In particular, solar energy production is ramping up, contributing to 3% of US energy production in 2019. However, smoke and dust from wildfires and other sources increase air pollution. This increase in air pollution reduces the amount of solar radiation reaching the earth's surface, thereby reducing the amount of energy produced by solar power stations. This work studies the relationships between particulate matter (pm2.5) and aerosol optical depth (AOD) on solar radiation measurements.

This poster will focus on quantifying the effects of aerosol and particulate matter pollutants on solar irradiance. In particular, we consider air quality data from several EPA stations across the United States and Aerosol Optical Density (AOD) from NASA MODIS satellites. As a proxy for photovoltaic energy production at each site, we use solar irradiance measured by the identical MODIS satellites. The goal is to provide reasonably realistic estimates of how aerosol and pm2.5 pollutants affect the performance of a PV module using a simple regression model and cluster together locations with similar contaminants.

Problem Area

In the last few years, fossil fuel has continued to deplete, and there is a global effort to move towards other forms of energy - specifically sustainable and non-polluting ones. Government agencies around the world are pushing to move toward renewable energy sources for several reasons. First, unlike nuclear and fossil fuel sources, renewable energy sources such as wind and solar are highly susceptible to local effects. For instance, wind direction and speed impact how much wind energy are produced. On the other hand, atmospheric variables such as pollution, precipitation, etc., can impact solar energy production (Liu et al., 2018). Thus, it is crucial to reliably model and understand the effects of atmospheric conditions on solar energy production.

Exploratory Data Analysis



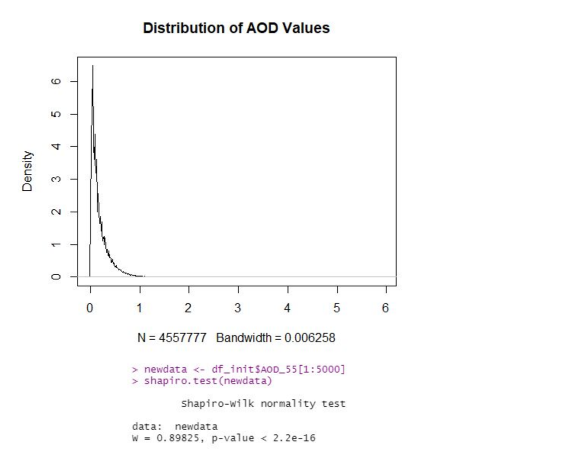
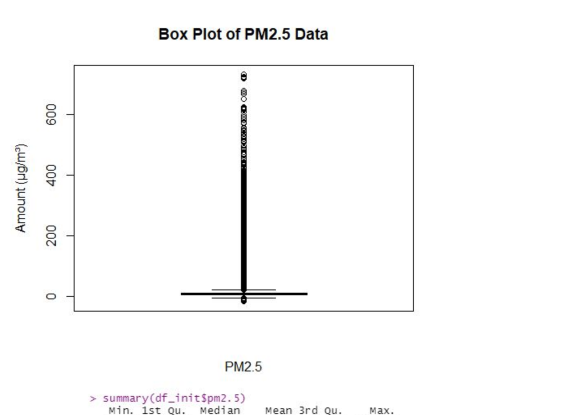


Figure 3(left): Density plot of unit PM2.5 with corresponding Shapiro test results

Figure 4(right): Density plot of unit AOD with corresponding Shapiro test results



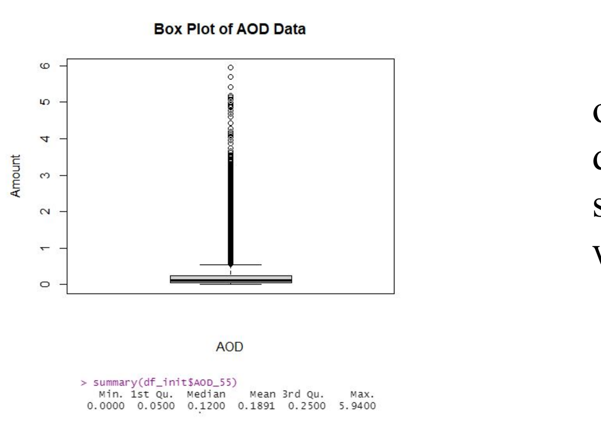
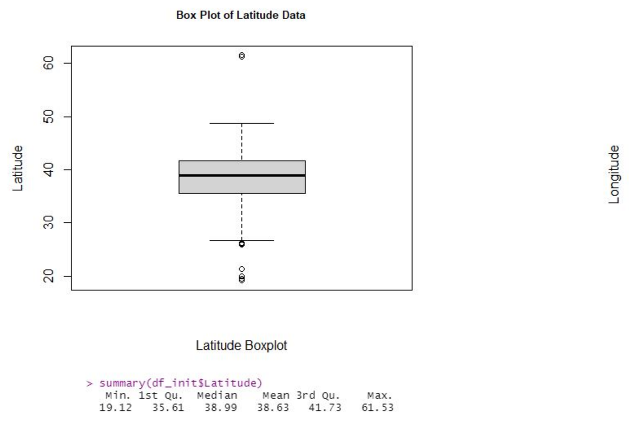


Figure 5 (left): Box plot of unit PM2.5 with corresponding statistic summary

Figure 6 (right): Box plot of unit AOD with corresponding statistic summary



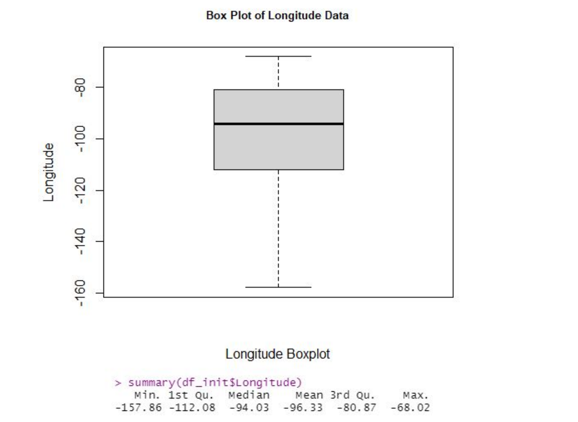


Figure 7 (left): Box plot of latitude with corresponding statistic summary

Figure 8 (right): Box plot of unit AOD with corresponding statistic summary

Works cited:

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Donaldson, D. L., Piper, D. M., & Jayaweera, D. (2021). Temporal solar photovoltaic generation capacity reduction from wildfire smoke. *IEEE Access*, *9*, 79841–79852.

Gaetani, M., Huld, T., Vignati, E., Monforti-Ferrario, F., Dosio, A., & Raes, F. (2014). The near future availability of photovoltaic energy in Europe and Africa in climate-aerosol modeling experiments. *Renewable and Sustainable Energy Reviews*, *38*, 706–716.

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Data

a) We combine historical measurements of aerosol optical density (AOD) with weather and pollution data (pm2.5) with the goal of understanding what effects these have on solar irradiance measures. In particular, we considered hourly measurements of these datasets for the entire year of 2019. Particulate matter (pm2.5) measurements were downloaded from the Environmental Protection Agency's (EPA) AirData webpage (https://aqs.epa.gov/aqsweb/airdata/download_files.html). After filtering for locations that report hourly pollution measures, we ended with 808 stations (Figure 2). Using each station's latitude and longitude values, we query NASA's POWER API (https://power.larc.nasa.gov/) using a RESTful API based python script to download AOD, weather and solar irradiance measures.

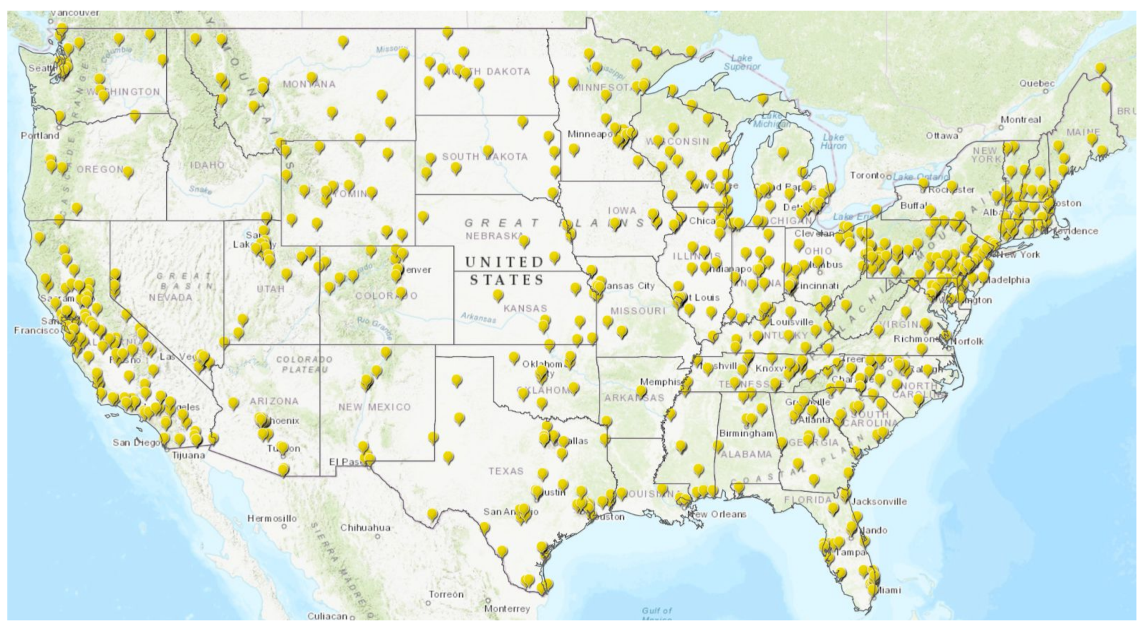
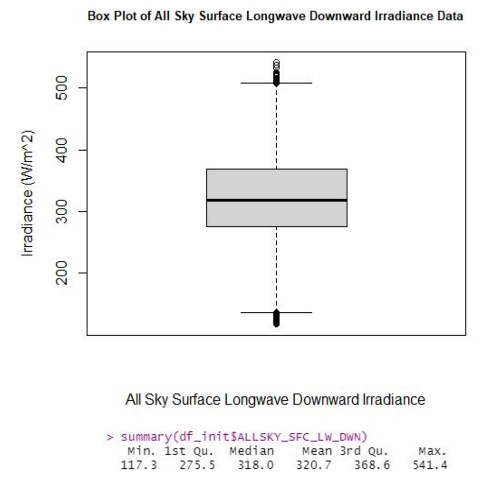


Figure 2: Particulate matter (pm2.5) measuring stations around the United States.

Each of these datasets was downloaded in comma-separated values (.csv) format and aligned using a unique ID associated with each station (AQS_Site_ID). Originally, MODIS data from NASA's POWER API were separated for each weather station, and metadata was at the top of each .csv file. We removed the metadata header and moved that to a separate .xml file using Dublin Core metadata standard appending metadata information from EPA pm2.5 as well. The date and time of data points were standardized to ISO 8601 standards for easier matching between datasets.

Conducting Analysis



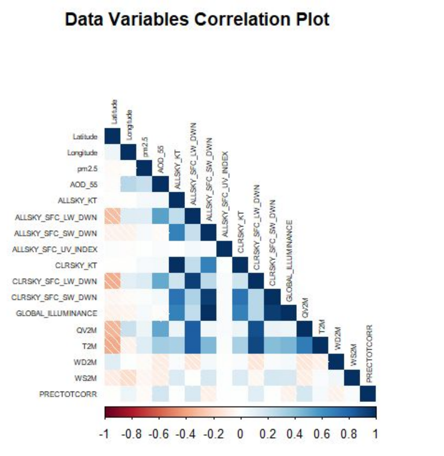


Figure 9 (left): Box plot of irradiance data with corresponding statistic summary

Figure 10 (right): Data variables correlation plot with corresponding legend

Overall, the exploratory data analysis yielded that there are no blatant outliers in our data that can significantly change any possible conclusion derived; and with the details of the data given regarding key relationships such as association and distribution, we have formal evidence to proceed with future appropriate data regressions and modeling.

Predictions and possible decisions

When taking steps to increase solar energy production in the future, efforts must be made to analyze the effects of air pollution caused by smoke and dust from wildfires, precipitation, and other factors on solar irradiance. In our study, we have determined there is a low correlation between PM2.5 and AOD through Lasso-Ridge regression. In regards to trends observed from regional clusters, the Southeast exhibited the least variance in the data which implies a more stable climate whereas the Northeast exhibited the most variance in the data. Increasing variations indicate a less stable climate, which could occur due to natural phenomena such as hurricanes, shifting seasons, and changing climates. When looking at the mean, the West coast region has the highest average compared to the Southeast which has the lowest average. This implies the sun appears less in this region, which may occur due to weather variations or natural phenomena like storms. Overall, our work is intended to provide relevant analysis to policy makers and developers involved in new PV generation sites and to provide a basis to hypothesize about trends across different regions of the U.S.

Model Application

Thus, the 2 models applied were ridge and lasso regressions, shown below:

Lasso Regression:

Mean Squared Error by λ value

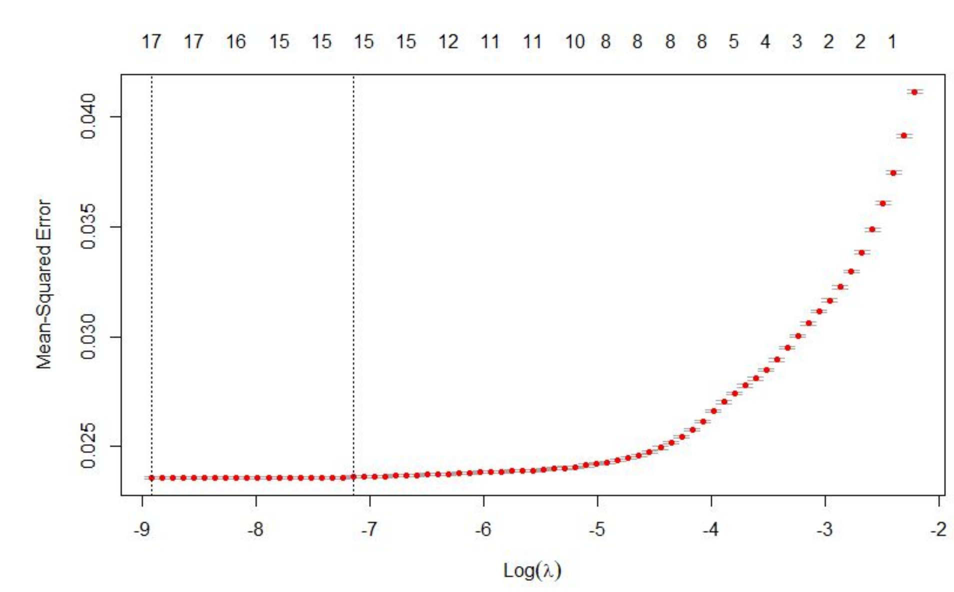


Figure 11: Lasso Regression of PM2.5 and AOD Correlation

Ridge Regression:

Mean Squared Error by λ value

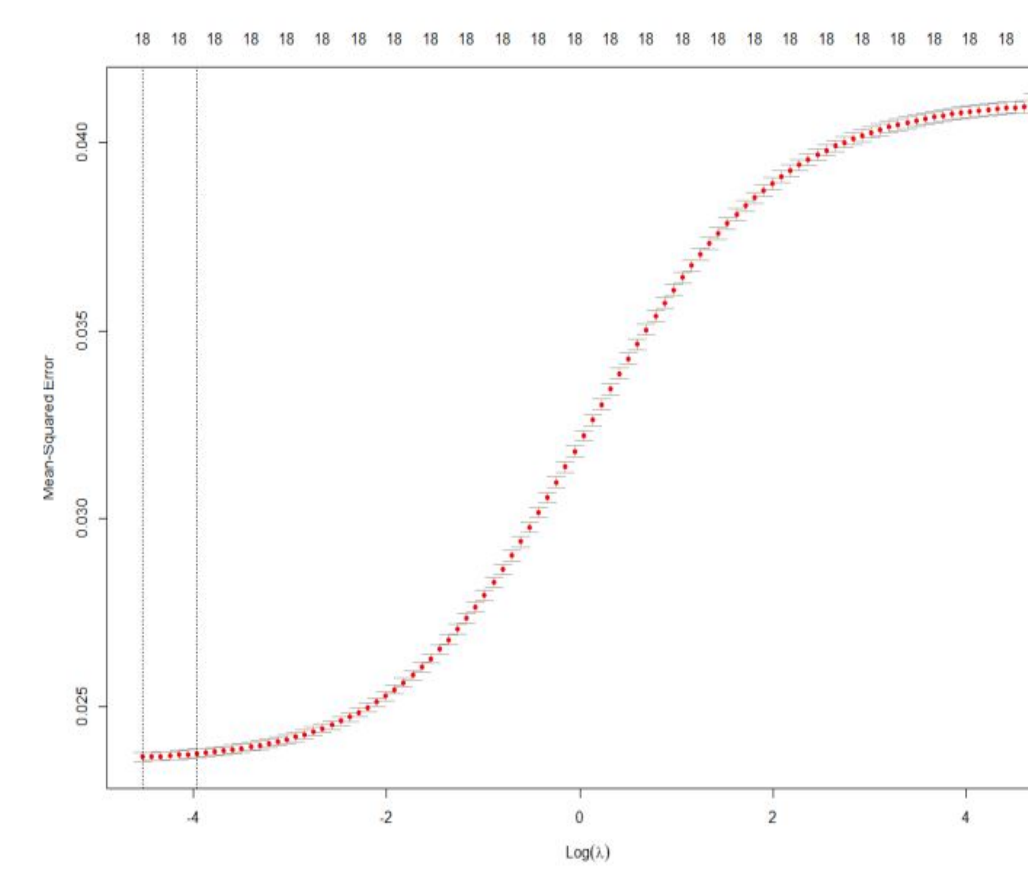
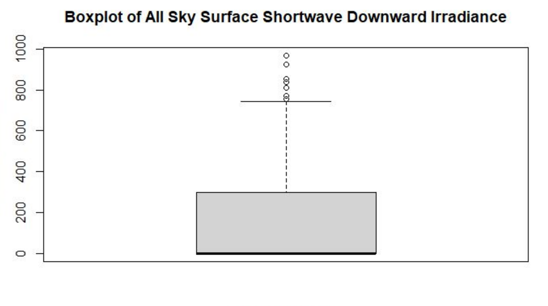


Figure 12: Ridge Regression of PM2.5 and AOD Correlation

As previously mentioned, the PM2.5 and AOD values diverge significantly from normal distribution such that Lasso-Ridge is the appropriate model to prove a significant correlation between the two values. When analyzing the correlation between PM2.5 and AOD values using Lasso regression the resulting R^2 value is 0.42. R^2 =0.42 is an indicator of low correlation between the two values. The low log(λ) values indicates there is less need to induct penalties on the data. The Ridge regression model yielded an R^2 value of 0.43.



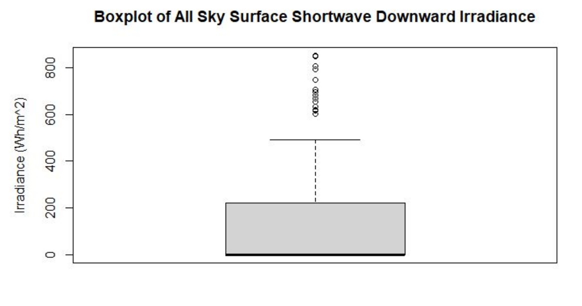
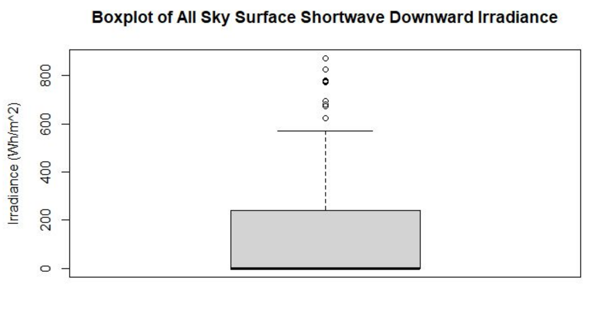


Figure 13 (left): Box plot of solar irradiance, Mean = 147.30, Standard Deviation = 271.94

Figure 14 (right): Box plot of solar irradiance, Mean = 141.50, Standard Deviation = 231.42



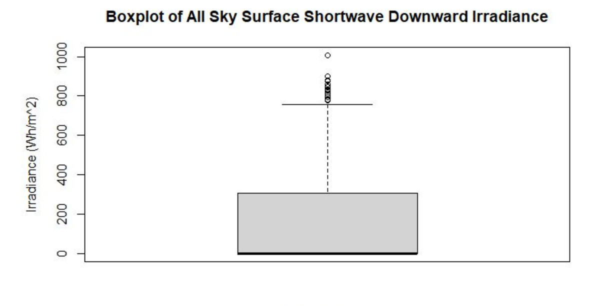
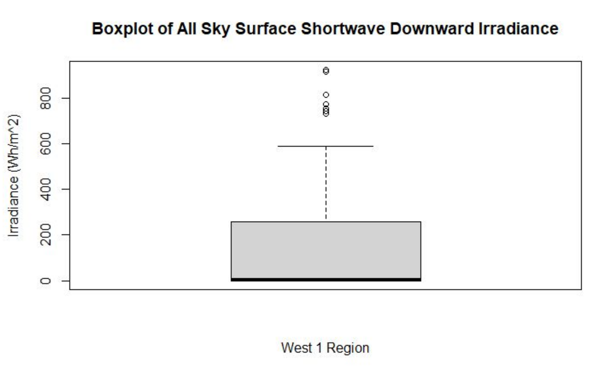


Figure 15 (left): Box plot of solar irradiance, Mean = 176.50, Standard Deviation = 269.06

Figure 16 (right): Box plot of solar irradiance, Mean = 163.20, Standard Deviation = 247.75



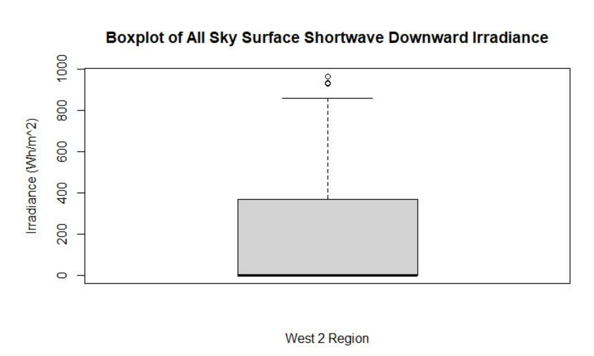


Figure 17 (left): Box plot of solar irradiance, Mean = 166.62, Standard Deviation = 259.88

Figure 18 (right): Box plot of solar irradiance, Mean = 179.20, Standard Deviation = 258.66