Studying the effects of wildfires and other pollutants on solar energy production (Group 8)

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1 (a) Abstract

Although the world still relies on fossil fuel combustion for the majority of 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 contribute to increasing air pollution. This increase in air pollution reduces the amount of solar radiation reaching earth's surface, and thereby reducing the amount of energy produced by solar power stations. In this work, we study the relationships between particulate matter (pm2.5) and aerosol optical depth (AOD), along with latitude and longitude values and solar radiation measurements. In particular, we first built a regression model to find the relationship between pm2.5 readings from weather stations across the United States and AOD measurements taken from MODIS satellites and found a significantly low correlation between these two variables. We also cluster locations based on similar latitude and longitude values to find regional similarities in terms of solar irradiance and found the Northeast United States region experienced the greatest variance in irradiance, but the far West United States region experienced the greatest average in irradiance. This work is aimed at researchers and

policy-makers to analyze and interpret the risk factors such as pollution and solar energy production. As we move towards a renewable energy dominant future, it is essential to balance this loss in energy through predictive grid optimization.

1 (b) Introduction

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 towards renewable energy source for several reasons: (i) reduce our carbon footprint as a commitment towards a greener future (Cozzi et al., 2020), (ii) cope with the increasing demand for energy around the world, (iii) global instability caused by countries that hold fossil fuel reserves (Seljom & Rosenberg, 2011), etc. Worldwide forecast of energy production says that 18-40% of demand will be supplied with renewable sources. In the United States, solar energy comprised about 14% of the renewable energy portfolio in 2019, and it currently makes up nearly 3% of the total energy production. Amongst various sources solar photovoltaic and wind energy are expected to significantly contribute to global energy mix in the future (Crook, Jones, Forster, & Crook, 2011; Gaetani et al., 2014). 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 has an impact on how much wind energy is produced. On the other hand, atmospheric variables such as pollution, precipitation etc., can impact solar energy production (Liu et al., 2018). Thus it is important to reliably model and understand the effects of atmospheric conditions on solar energy production.

In the near future, photovoltaic (PV) solar energy production is expected to grow rapidly in comparison to other sustainable sources (Crook et al., 2011; Gaetani et al., 2014). Specifically in regions with high levels of dust and pollution (Bergin, Ghoroi, Dixit, Schauer, & Shindell, 2017). Solar irradiance and temperature at PV modules are known to be the main contributors of PV performance, with spectral distribution a close second (Moreno-Sáez, Sidrach-de-Cardona, & Mora-López, 2016) (Liu et al., 2018). On a clear day, solar irradiance and temperature are modulated by the contents in aerosols and particulate matter pollutants (Gaetani et al., 2014).

In this work, we 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 located 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 same MODIS satellites. The goal is to provide fairly realistic estimates of how aerosol and pm2.5 pollutants affect the performance of a PV module using a simple regression model and potentially cluster together locations that have similar levels of pollutants. This will better inform policy makers and developers when they consider setting up new PV generation sites.

1 (c) Literature Review

[Paper 1] In this paper (Bertoletti, Phan, & Campos do Prado, 2022) describes the impact of the 2020 wildfire in Washington state and the effects on air quality and renewable energy. It is similar to the search that we are doing in our final project because we will also examine the wildfire and the impact of wildfire on renewable energy, which is solar energy. After all of the research, it has been noticed that solar power generation facilities may not be located in high fire risk zones, but they may still be affected by the traveling smoke from far away wildfire smoke on solar energy during the 2020 Washington state wildfire. They have also noticed a decrease in wind speed and air quality index. As a result, their research highlights the need for more resilient planning and preparation for wildfire events, especially for policymakers, infrastructure planners, and power system operators who seek to promote and integrate clean and renewable energy sources with increased reliability and resilience. In conclusion, their work demonstrates that PV production can be significantly impacted during times of increased concentration of wildfire smoke and reduced wind speeds. We intend to examine alternative power generating options and their effects on air quality while determining the best power system operation techniques for areas affected by wildfire smoke.

[Paper 2] This next paper (Gómez-Amo et al., 2019) evaluates the effect of two types of aerosols - dust and smoke on photovoltaic (PV) energy production during an episode of extreme wildfires and dust in Spain during the summer of 2012. This study deviates from the others by relying solely on data and no modeling is involved. For data, they use PV measurements from a station in the University of Valencia, and aerosol-related data, such as aerosol optical depth (AOD), Angstrom exponent (AE) etc, were measured at a nearby station. For analysis, they measured how PV deviated from reference values using several metrics calculated using measured data. They found that the PV production was reduced as much as 73% from smoke and 12% from dust in comparison to a reference day. We intended to expand on the work done in this paper by adding daily energy production data from other sources such as nuclear, natural gas, coal etc. We could potentially use the same metrics and study the relationship between how the total energy production was compensated due to loss in solar energy generation. Additional modeling could be done to predict the impact of future wildfire events on energy production.

[Paper 3] The objective of the next paper (Juliano et al., 2022) is to view the impact of biomass burning aerosols and the quantitative impact of smoke emissions on solar energy fore-casting. Specifically, this paper uses national scale observational networks and an NWP model. The paper uses data from the Surface Radiation Budget Network and the Solar Radiation stations and provide information on global horizontal irradiance (GHI) and DNI. It is worth noting that although this paper does focus on forest fires and their impact on solar radiation, it heavily examines the use of biomass-burning aerosols. This presents a deviation from our work as our work avoids a focus on aerosols.

[Paper 4] Next paper (Gilletly, Jackson, & Staid, 2021) aims to show that the reduction of solar photovoltaic energy production with the presence of wildfires and resultant smoke is significant on a 95% confidence interval. This paper used solar PV energy production sites from the PVROM database relevant in terms of location, PM2.5 particle count data supplied by the U.S. Air Quality Index department, and weather data from the NASA Prediction of Worldwide Energy Resource including, but not limited to, average temperature, wind speed and direction, and amount of precipitation. Using all this data, the paper then proposes a regression model held at a 95% confidence interval to determine if more smoke in the air (measured in PM2.5 particle count) significantly indicates a decrease in solar PV energy production. This paper performs a stellar job detailing all the data it collected, the regression model it used to analyze such data for its conclusion, and several possible significant factors it may have missed in terms of calculating solar PV energy output (e.g. residual ash). Overall, we can utilize this paper's conclusions, methods, and analysis in order to heighten our own research on the effects of wildfires on energy production not limited to solar PV energy, as well as build off this paper's research on the specifics of how better to manage energy production during such hindrances.

[Paper 5] This paper (Donaldson, Piper, & Jayaweera, 2021) aims to investigate the temporal effects wildfire smoke has on photovoltaic energy production, which entails understanding how much wildfire smoke's magnitude and duration influences a derate in PV generation. In terms of datasets, the authors used sources for two cases: one short period of intense fire activity in California from September 1 to September 14 and one long period from August 1 to September 28. They sourced major fire perime- ters from the National Interagency Fire Center, solar PV generation in Califor-nia from SCADA for 10 different facilities in 4 geographic areas, weather data comes from NASA's MERRA-2 renalysis, clearsky GHI from the National So-lar Radiation Database, and satellite data from NOAA's GOES-17 satellite. In terms of models, the authors used quantile regression as the main model and compared its accuracy against linear regression and piecewise linear regression. In terms of techniques, the authors compared the models through stratified k- fold cross-validation (k = 10) as this problem is inherently unbalanced alongside the mean average error for each model across both the two-week period and the two-month period. They also made sure to normalize across three stages: season, weather, and min/max power output. This paper is related to our group project proposal as it too sits at the intersection of wildfires and energy generation. In this sense, we could take in- spiration from data sources, models, and techniques to use. We would want our project to be more general in terms of energy; this paper focuses on PV generation. We may want to include PV generation, but we also want other resources like wind and geothermal energy. That way, we may view what share each re- newable takes up and how they synergize with each other.

[Paper 6] This paper by (Rieger et al., 2017) analyzed dust occurrences over Germany by combining aerosol and pollution measurements and prediction modeling. By adding dust related measurements, they reported an overall 65% improvement in PV energy production. In particular, they observed that dust contributed for 64% of PV output losses while a 20% was due to other indirect effects, and the rest was attributed to synergetic effects.

[Paper 7] In a paper by (Perry & Troccoli, 2015), the authors study aerosols produced by fire burns and their impact on both solar irradiance and solar power. Global and direct irradiance observations on event day were compared with those from analogous clear days, and irradiance values obtained by a clear sky model. Through this analysis, the authors found a 6.5% reduction in global irradiance and 9% direct irradiance. Consequently, PV output saw an overall reduction of 7% during the study period.

[Paper 8] A paper by (Bergin et al., 2017) studied high levels of dust and other anthropogenic pollutants over China, India and Arabia found an annual PV energy reduction around 17–24% with equal contribution of aerosols suspended in the atmosphere and particulate material deposited on solar modules.

1 (d) Project Workflow Diagram

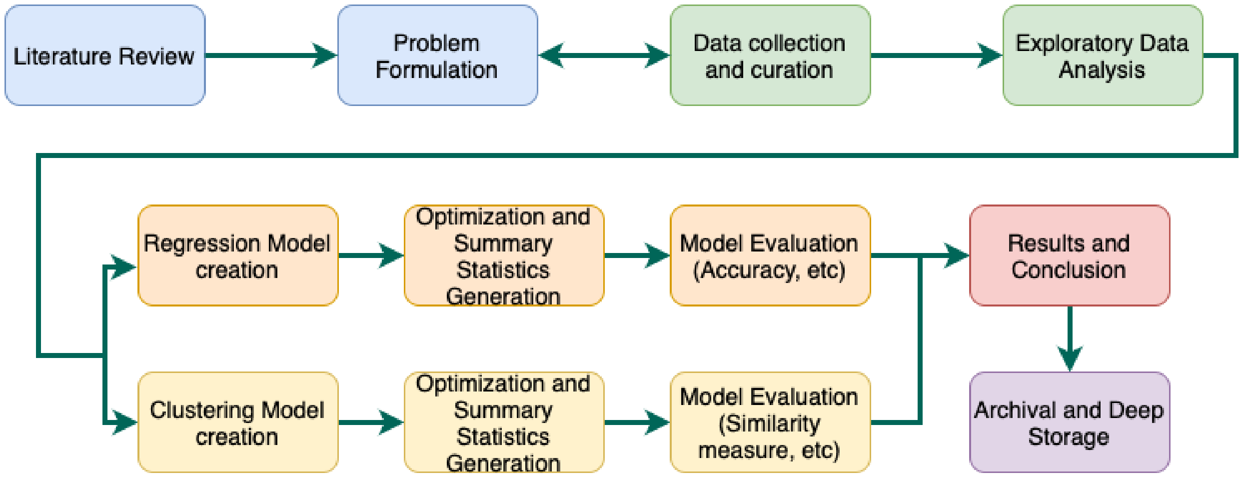


Figure 1: Workflow diagram highlighting different steps in the project pipeline.

In literature review and problem formulation we worked on reading existing papers in the area of interest as cited in the Literature Review section and formed the problem statement. We then proceeded to collect data from different sources, specifically EPA (Environmental Protection Agency) and NASA. We had to adjust our problem statement to account for un availability of solar energy generation data, which is why the arrow is bi-directional. Next we conducted Exploratory Data Analysis and built our models. After training each model, we optimized these models, generated summary statistics and evaluated them. Finally results and conclusions were generated and we plan to archive data and code for long term storage.We used the workflow tool https://draw.io to generate this diagram.

2. Data Description and Methodology

2 (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.

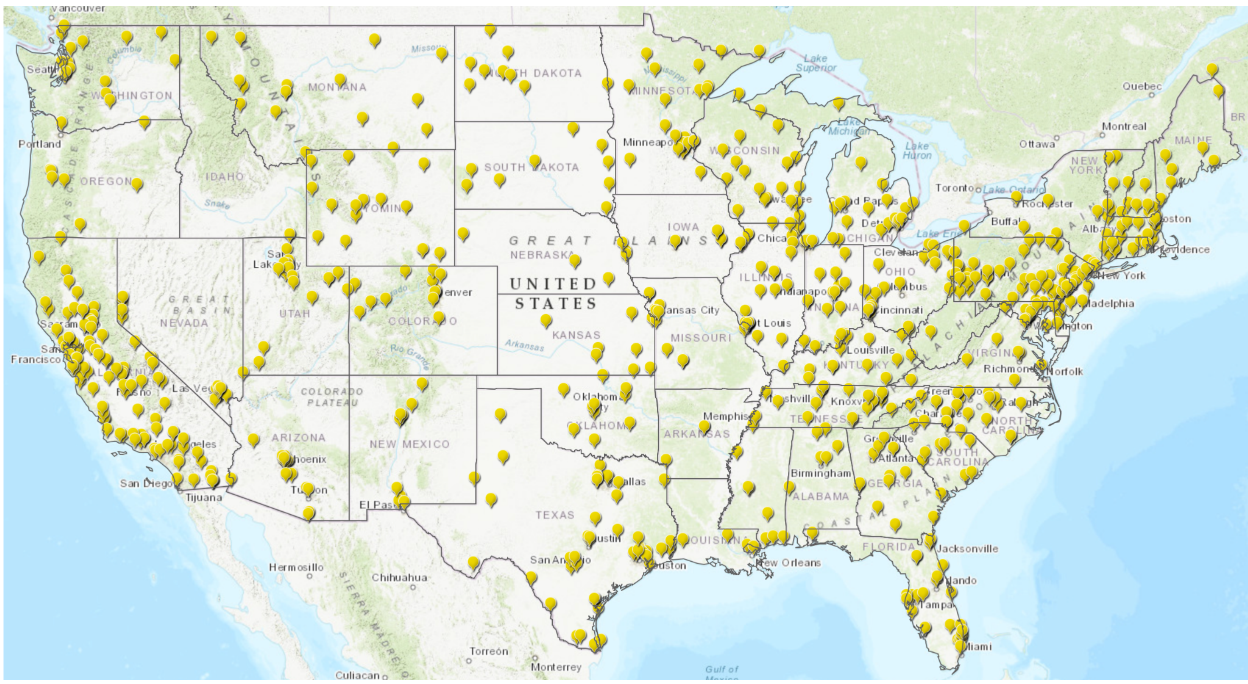


Figure 2: Particulate matter (pm2.5) measuring stations around the United States.

2 (b) 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.

3. Data Analysis and Explore the statistical aspects of your datasets

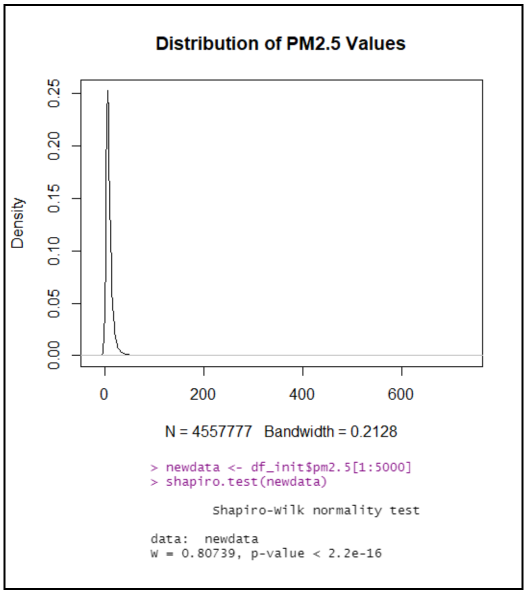
3 (a) In this work, we aim to answer two key questions.

We aim to prove the existence of a significant correlation between PM2.5 and AOD, both units of which are used to measure air pollution through particle density. The preliminary step in accomplishing this task is to determine if the data regarding PM2.5 and AOD are of normal distribution. This can be accomplished by running a Shapiro statistical test at the 95% confidence level for both PM2.5 and AOD data respectively; if the corresponding p-value yields a value less than 0.05, we reject the null and conclude at a 95% confidence level that the data is not normally distributed. Once normal distribution significance is established, we aim to perform the proper regression technique with respect to outcome in order to demonstrate significant correlation between the two variables. This regression test will ultimately be the deciding factor in providing an answer to our query; we will again be regressing under a 95% confidence level for the regression as well. Our null hypothesis is that there is no significant correlation between units PM2.5 and AOD, and it will promptly be rejected should the p-value yielded from the regression turn out to be less than 0.05. In context, we can confirm with 95% confidence that there exists a significant correlation between units AOD and PM2.5 if such a p-value is yielded. In application, we have a definitive answer to our query stated earlier, and can state a case for future research that either unit works when describing air particle density because of the existence of significant correlation. Furthermore, we aim to perform regressions relating both air particle density units to solar irradiances to demonstrate the flexibility obtained by our described regression.

We also aim to study common trends of different regions of the United States with respect to solar irradiation through cluster analysis that may be found. For clarification, we raise a question regarding the existence of common trends of different regions (represented by latitude and longitude defined boundaries), the answer of which can be identified through the clustering of said regions and the analysis of the corresponding data inside said clusters and any trends of interest regarding solar irradiation. This is accomplished by obtaining latitude and longitude data and their corresponding PM2.5 and AOD data, as well as long-wave and short-wave solar irradiance of different sky conditions, with separate data for the clear sky condition as well. Once this preliminary step is completed, the analysis then proceeds to "cluster" different regions of the United States using this latitude and longitude data and marking different observations noted during the clustering process. After this analysis has been conducted, the post-analysis study will consist of raising questions with respect to the trends noted. It is important to note that cluster analysis in theory does not seek to answer any formal hypothesis; rather, it identifies common trends and observations of interest as a stepping stone to building said hypotheses. Consequently, we answer the base question behind this study by identifying such trends, concluding the existence (or lack thereof) of trends in separate geographical clusters.

3 (b) As preparation for executing such experiments, proper exploratory data analysis must be performed.

For query 1, the matter of determining whether the data for air particle units PM2.5 and AOD is one of high importance, since the result completely influences the type of regression necessary to prove significant correlation. Figure 3 shows a density plot made for unit PM2.5 with corresponding statistics described directly below the graph, and Figure 4 shows the same for air particle unit AOD. From the Shapiro test results shown in Figure 3, we conclude at a 95% confidence level that the distribution for unit PM2.5 is not normal, as the p-value yields a value much less than the earlier defined standard of 0.05. Similarly, we conclude the same for Figure 4, as the p-value is less than 0.05 as well. Since both of these values are significantly not of normal



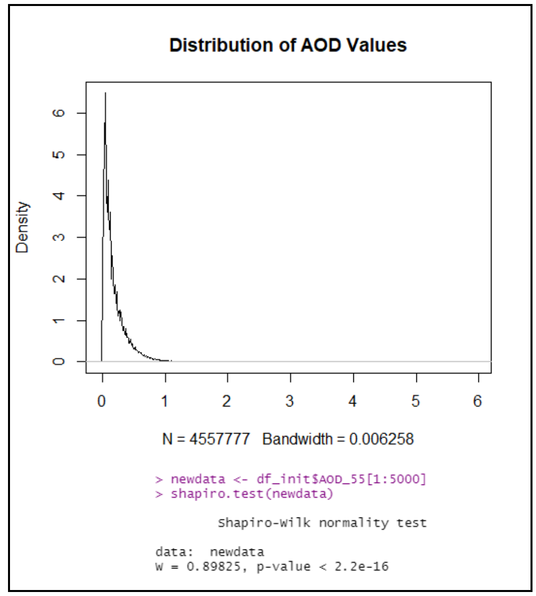
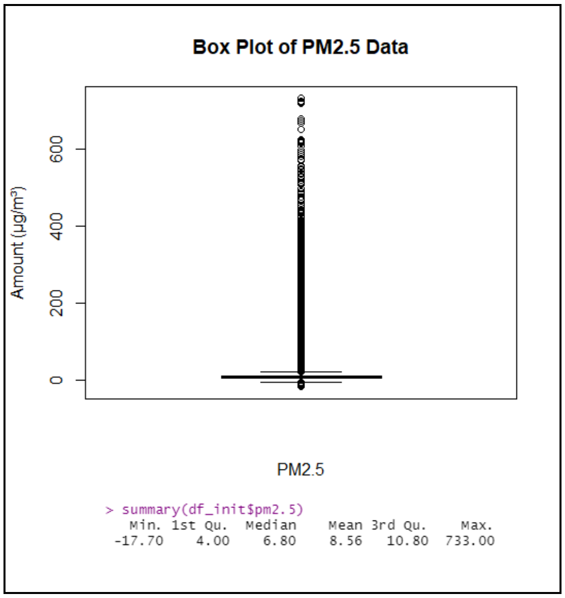


Figure 3(left): Density plot of unit PM2.5 with corresponding Shapiro test results

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

distribution, the Lasso-Ridge regression is the appropriate model for proving significant correlation between the two air density units. Additional barplots for the air density units are also provided in this report, due to their significance in this study. Figure 5 shows a barplot of all the PM2.5 values, with the corresponding summary attached. Figure 6 follows the same format as Figure 5, but for AOD values. Upon a cursory inspection, the data looks to be reasonable - according to the New York State Department of Health, the long-term standard (annual average) for air quality standards was revised in 2012 to be 12 µg/m^3. As the mean is around 8.5 µg/m^3, it can be asserted that the air quality in the United States is relatively healthier on average when analyzing the air quality data with PM2.5 units, yet within reason. Additionally, the Global Monitoring Laboratory of the National Oceanic and Atmospheric Administration asserts that the average air particle quality in the United States in AOD units is around 0.1 to 0.15. As the mean from our data is around 0.19, it can also be asserted that the air quality in the United States is



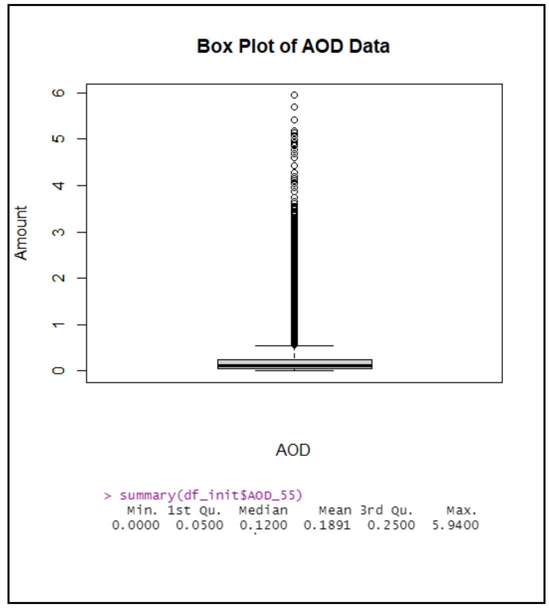
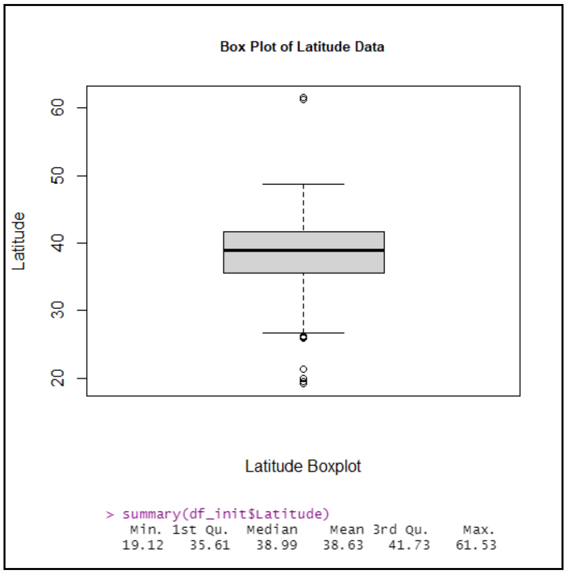


Figure 5 (left): Box plot of unit PM2.5 with corresponding statistic summary

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

relatively unhealthier on average when analyzing the air quality data with AOD units, again within reason. Outliers in the data as shown by the box plots symbolize areas in the United States where the air particle density is higher and consequently more lethal. For example, a PM2.5 reading of 600 µg/m^3 could symbolize the location of a wildfire or tornado. Ultimately, we conclude from the exploratory data analysis that the data is reasonable and appropriate for conducting the proper statistical analyses used to answer query 1.

For query 2, the cluster analysis requires the latitude and longitude data, as well as the solar radiation data, since these are the values of interest for providing an answer. Figure 7 shows a boxplot of the latitude data with corresponding statistics, and Figure 8 shows a boxplot of the longitude data with corresponding statistics. As the spread of the latitude and longitude data line up with the latitude and longitude spread covering the United States with minimal outliers, it appears that the latitude and longitude data provided are reasonable. Figure 9 shows a boxplot of



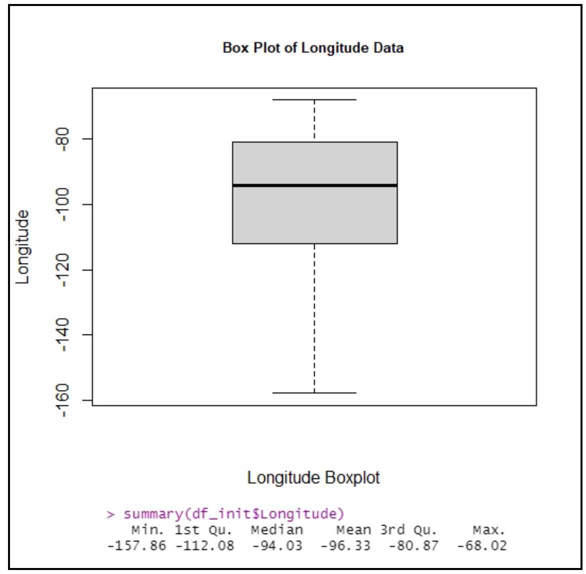
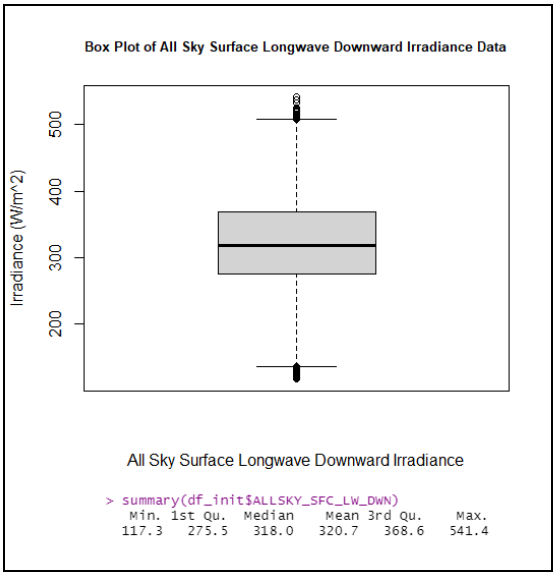


Figure 7 (left): Box plot of latitude with corresponding statistic summary

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

the solar irradiance data with corresponding statistics; from a cursory view, it appears that most of the data has been encapsulated by the boxplot range with a handful of outliers. Since there are no blatant outliers in the data, we may proceed with the cluster analysis while carefully noting that the outliers may have an influence on the overall results derived.

Finally, Figure 10 shows a correlation plot between all relevant variables. Indeed, the legend in Figure 10 provides context towards a direct relationship between correlation and color shade - in essence, the color red yields a negative association between two variables and the color blue a positive association, with a deeper shade of the respective color symbolizing a closer approximation to a perfectly linear relationship. From this correlation plot, we gather that the PM2.5 and AOD values have a positive association that is around equal to 0.2, and that the association between the shortwave downward irradiance for all skies and the air density unit AOD is higher than that of the association between the shortwave downward irradiance for all skies and the air density unit PM2.5.



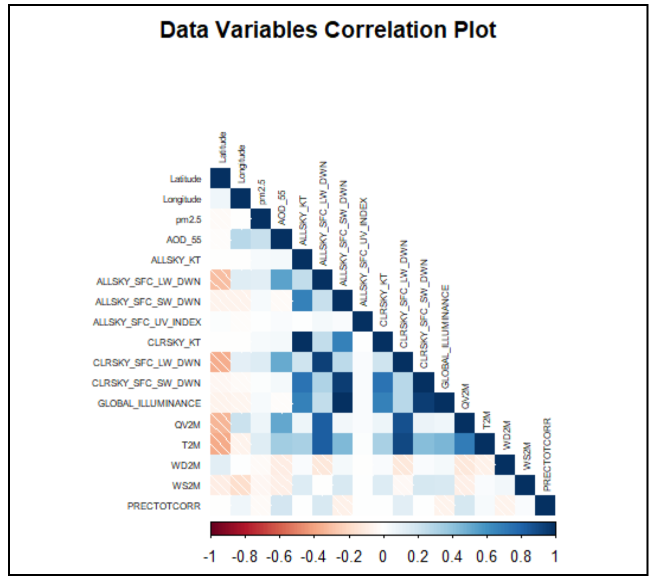


Figure 9 (left): Box plot of irradiance data with corresponding statistic summary

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.

4. Question 1: Can AOD be used to predict PM2.5 (using the Lasso-Ridge regression model)?

As previously mentioned, the PM2.5 and AOD values diverge significantly from a normal distribution. Additionally, there is a high level of intercorrelation. Therefore, lasso regression and ridge regression constitute the appropriate model to prove a significant correlation between the two values.

The analysis between PM2.5 and AOD values yielded extremely low R^2 values for both ridge regression and lasso regression which remained around 0.02. When all other independent variables were included, the resulting R^2 value of lasso regression was 0.42, indicating a low goodness of fit between these values. The log(λ) value of the lasso regression was -7.2 which indicated a low penalty on the data which indicates a low spread of values.

In contrast to lasso regression, the ridge regression model yielded an R^2 value of 0.43. However, ridge regression yielded a log lambda value of -4.0 which signifies a higher penalty associated with the variables which, in turn, constitutes a higher variance.

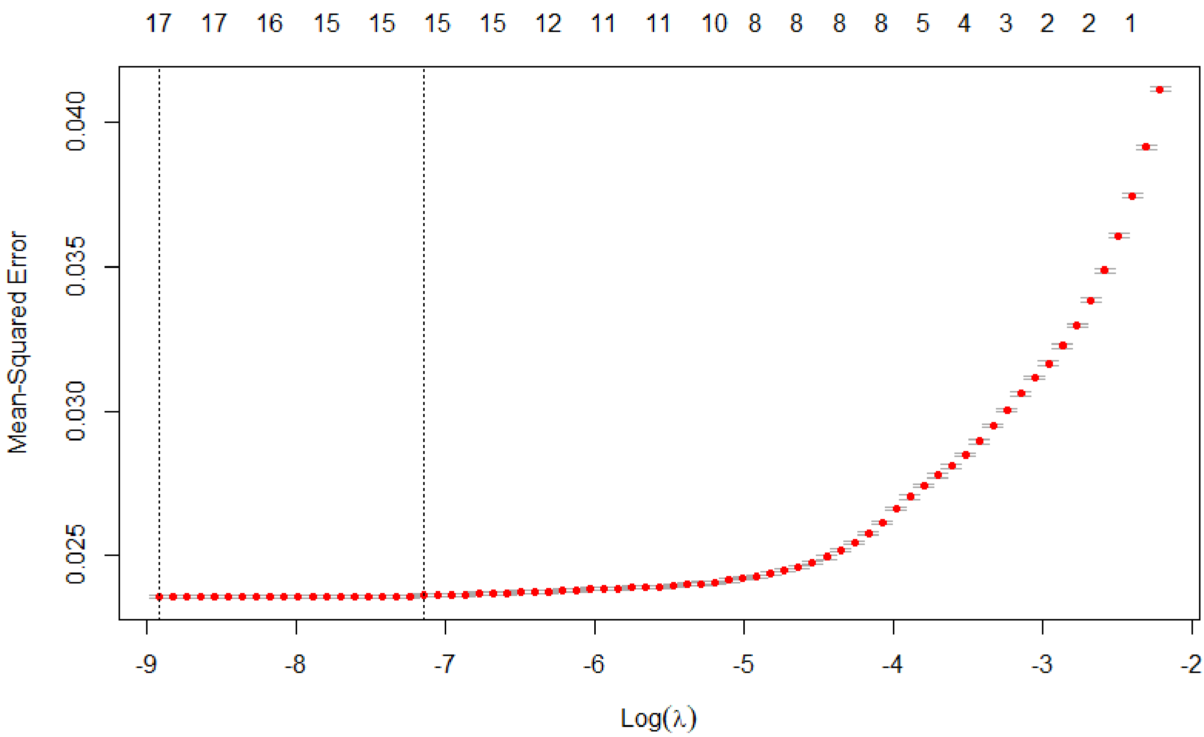


Figure 11: Lasso Regression of PM2.5 and AOD Correlation

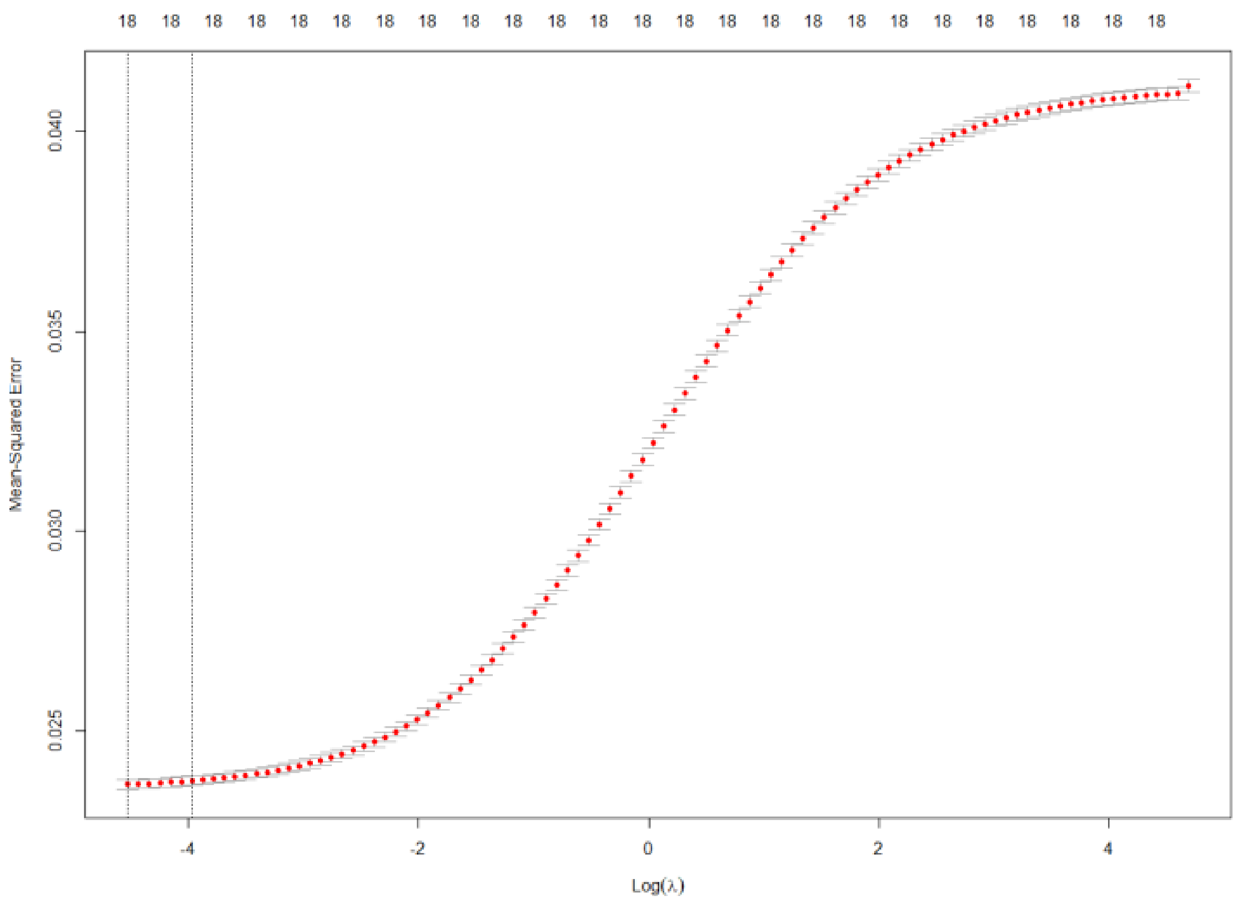


Figure 12: Ridge Regression of PM2.5 and AOD Correlation

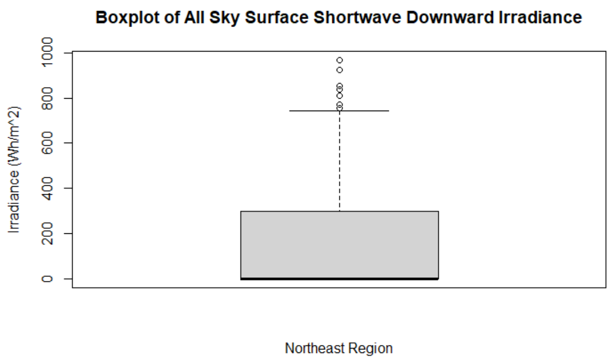
5. Question 2: Do there exist possible trends in air pollution in different regions of the United States?

To investigate this, we needed to split the Continental United States into six rectangular clusters and sample a thousand points. These regions are illustrated in Figure 13. For each of these six rectangular clusters, we generated box plots, summarized key metrics (specifically the mean) about the shortwave downward irradiance, and calculated standard deviations. It is from these that we can base an analysis that answers the question.

To start, the Northeast region experiences an average irradiance of 174.30 Wh/m^2. Its

Figure 13: Continental United States Regions Used for Cluster Analysis

standard deviation, however, is 271.94 Wh/m^2. This region exhibited the most variance in the data. Increasing variations indicate a less stable climate. This can occur because of natural phenomena like severe storms, shifting seasons, and changing climates. At 141.50 Wh/m^2, the Southeast region has the lowest average irradiance. This implies the sun appears least often in this region, which may occur due to weather variations or natural phenomena like thunderstorms or hurricanes. Its standard deviation, meanwhile, is 231.42 Wh/m^2, which is the lowest among all regions. This implies that its climate is more stable than the others. The Midwest region reaches an average irradiance of 176.50 Wh/m^2 and a standard deviation of 269.06 Wh/m^2, and the similar values imply it has a similar solar prevalence and stability to the Northeast region. The Southwest region, with its average irradiance of 163.20 Wh/m^2 and standard deviation of 247.75 Wh/m^2, represents a less sunny and more stable climate in line with the Southeast region. West 1 represents similar sun exposure with greater variance as its average irradiance is 166.62 Wh/m^2 and standard deviation is 259.88 Wh/m^2. West 2, meanwhile, features the largest average irradiance of 179.20 Wh/m^2. This is indicative of how often it is sunny and hot in this region, which makes it the ideal region to set up photovoltaic production facilities. This comes with some climate stability as its standard deviation is 258.66 Wh/m^2.



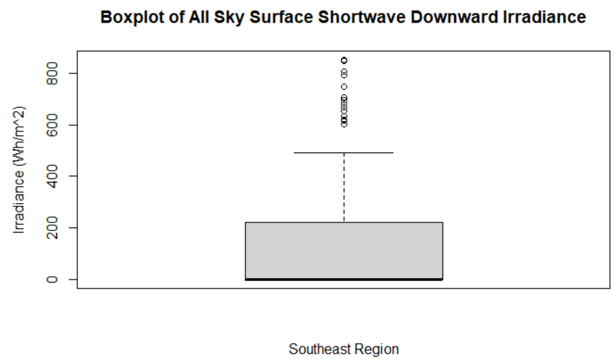
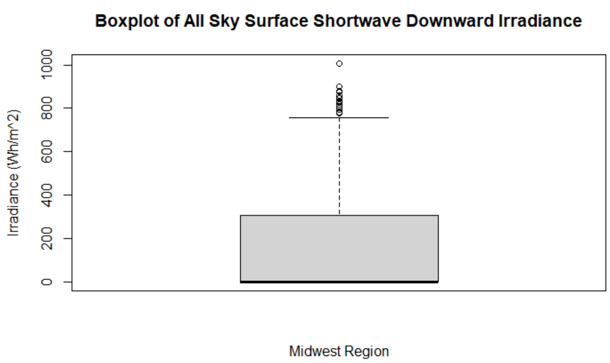


Figure 14 (left): Box plot of Northeast irradiance data

Figure 15 (right): Box plot of Southeast irradiance data



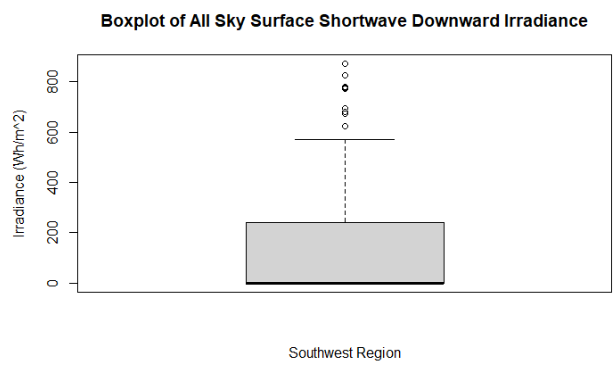
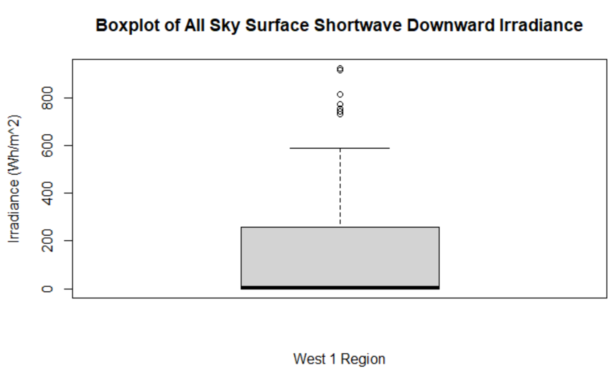


Figure 16 (left): Box plot of Midwest irradiance data

Figure 17 (right): Box plot of Southwest irradiance data



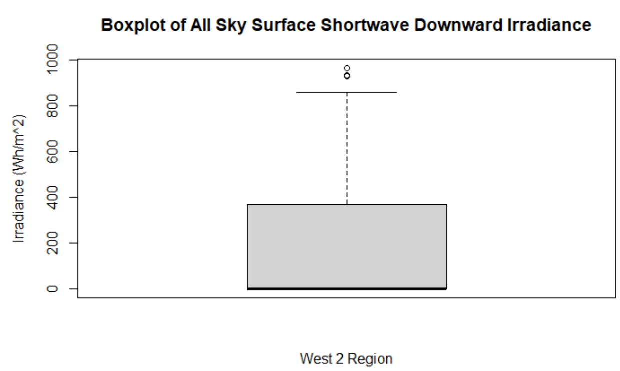


Figure 18 (left): Box plot of West 1 irradiance data

Figure 19 (right): Box plot of West 2 irradiance data

Wildfires may in some part contribute to larger variances and/or larger averages, but this could also be due to other natural phenomena like storms, seasons, or climates.

Discussion

In this study, we analyzed all of the PM2.5 and AOD data available to us. However, in future replications of the study, instead of combing through the entirety of the PM2.5 and AOD data, taking random samples of a sufficient amount would be appropriate due to the immense quantity of data. In addition, the study could be improved upon by having direct access to solar energy generation datasets instead of using solar irradiance by proxy. For the purposes of the study, we could not know how much energy each photovoltaic site produced because that would constitute a security breach. The tools and hardware used for the cluster analysis could also be changed for improving results. We used R for the cluster analysis and the intent was to originally map out the clusters on a map using longitude and longitude as independent variables and PM2.5 solar irradiance as dependent variables, but this was not possible in R so an alternative method to represent clusters based on location was needed.

Conclusion

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.

Repository: https://github.com/ITWSDataScience/Group8_2022

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