# Climate Change and Respiratory Risk in California's San Joaquin Valley

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## ABSTRACT

This study was conducted to inform how projected climate changes in the San Joaquin Valley (SJV) may affect public health by investigating the relationship between air pollution, temperature and asthma related hospitalization rates (ARHR). If a strong association exists between days of high temperature, high ozone concentrations and ARHR, this would link projected climate changes in SJV to asthma attacks. In this aim, I completed the following tasks. I built a Geodatabase in ArcGIS by collecting secondary data on ARHR, ozone, nitrogen oxides (NOx), temperature, and particulate matter 2.5 and 10 (PM 2.5, PM 10), which was used as a platform for the analysis. I determined the strength of association between temperature, air pollution and ARHR by comparing the resulting $R^2$ values from geographically weighted regression (GWR) and linear regression analysis looking at both the local variance and global relationships. I found that a combination of PM 2.5 and PM 10 resulted in the optimal explanatory model for ARHR in SJV ($R^2$ value of 0.7666). I determined that projected temperature rise coupled with high ozone concentrations do not indicate an imposing hazard in SJV by directly causing asthma attacks. However, the relationship between temperature, air pollution and ARHR is unclear so projected climate changes are still a concern. Further, by building an optimal explanatory regression model, identifying what air pollutants are of most concern for populations with asthma, counties in the SJV can efficiently allocate resources to alleviate the risk air pollution poses for asthma sufferers.

## KEYWORDS

climate penalty, temperature, air pollution, asthma, San Joaquin Valley

## INTRODUCTION

The San Joaquin Valley (SJV) is well known for having poor air quality in concurrence with extreme high temperatures. Here, pollution from agricultural, vehicular and industrial emissions becomes stagnant. Air pollution is trapped in the valley by an inversion layer that forms as a response to high temperatures; warm air rises and traps the cooler air beneath this inversion layer inhibiting pollution from leaving the valley. The pollution is so extreme that seven of the Valley's eight counties were included in the American Lung Associations 10 most ozone polluted counties in the nation in 2016 (State of the Air 2016). Kern County resides at the southern end of the SJV and is known for having the highest rates of asthma in the state and the third highest in the nation; it is estimated that 111,000 adults and children have asthma in the county (Schwartz and Pepper 2009, Milet et al. 2007). On average, from 2002 through 2004, each person in the Valley was exposed to unhealthy levels of ozone on 70 days a year, and in 2001 the city exceeded federal health standards for ozone for 109 days reaching a maximum level of 0.120 parts per million (ppm) (Hall et al. 2008; Meng et al. 2010). What temperatures were observed at these times, and how the catalytic relationship between temperature and ozone formation affected ozone concentrations remain unknown.

Complex interactions between temperature, ozone concentrations and asthma threaten to worsen the risk of asthma attacks and hospitalizations in Kern County. Extreme temperatures and heat waves affect asthmatics by acting as an environmental trigger of asthma attacks (Cody et al. 1992). Similarly, while ozone has not been found to cause asthma, it can trigger asthma attacks and hospitalizations by causing irritation to airways and lung tissues (Cody et al. 1992). Increased atmospheric concentrations of ozone along with nitrogen dioxide have been linked to increases in respiratory morbidity and in hospital admissions for asthma in children and adults (D'Amato et al. 2011; Meng et al. 2010). However, the relationship between ozone and asthma is complex and some studies have found that ozone pollution acts as a protecting factor when compared to hospital admissions – thereby demonstrating an inverse relationship between these variables (Bates et al. 1987). How these two variables together effect asthma attacks have not been investigated in detail. With two environmental triggers of asthma occurring simultaneously, asthma attacks might be increasingly exacerbated. Due to the EPA restrictions on emissions, ozone pollution along with NOX, PM 2.5 and PM 10 has been decreasing at a slow but relatively constant rate across the

United States, and this trend is consistent with observation in Kern County (United States Environmental Protection Agency 2012). Efforts to control precursor emissions of ozone have been successful in Kern County but with projected temperature rises within the next century, another gap is observed in understanding how a climate penalty of increased ozone concentrations will influence air quality despite these control efforts.

Temperature catalyzes the formation of ozone, and a positive correlation between these variables is well established. Sources of NOX and volatile organic compounds (VOCs) are vehicle exhaust and industrial emissions, gasoline vapors, and chemical solvents (Bell et al. 2013). Heat reacts with NOX and VOCs causing ozone to peak at times of the day when emissions spike. According to Thomas et al. (2009), a projected warming of 7 to 11 degrees Fahrenheit (F) in the United States can be expected by the year 2100. For the city of Bakersfield, one of the highest populated urban area in SJV, temperature, the number of heat waves and the number of extreme heat days is projected to rise over the coming century (California Energy Commission State of California 2015). As the number of extreme heat days increase, a climate penalty on ozone is observed exacerbating ozone concentrations. To restate, as temperatures and the number of extreme heat events rise, ozone concentrations will rise even if the precursor emission rate remains steady. Perera and Sanford (2011) calculated under moderate emissions scenarios an approximation of a 1.0 pbb ozone penalty by 2025 and a 2.0 ppb ozone penalty by 2050 for the United States. How this climate penalty on ozone will effect populations with asthma at the local level is not clear. Without a solid understanding, anticipating how this climate penalty places sensitive populations at risk is restricted. This inhibits the ability for SJV to make sensible policy decisions to avoid this health externality.

Similarly, Nitrogen Oxides and particulate matter have been found to exacerbate respiratory airways causing asthma attacks. In the San Joaquin Valley, diesel emissions along major transportation routes are the biggest source of particulate matter and nitrogen oxides. Specifically, PM 2.5 has been found to absorb deep in the alveoli of the respiratory tract and can be deadly if inhaled by sensitive populations such as those with asthma and this relationship is well supported by health studies (EPA 2016). In the 2016 State of the Air Report by the American Lung Association, Bakersfield Fresno and Merced were listed among the top five cities in the US with the highest number of days a year where particulate matter or ozone safety levels were exceeded. With other air pollutants interacting with ozone and temperature trapped underneath the inversion layer, populations with asthma in the valley are at a dire risk of experiencing severe asthma attacks resulting in death. The lack of understanding how the projected temperature rise will influence asthma inhibits the ability for SJV counties to make sensible policy decisions to protect those afflicted with asthma.

My research aimed to inform how projected climate changes in the SJV may affect public health by investigating the relationship between air pollution, temperature and ARHR. I expected that when temperature and ozone are at maximums, the association with ARHR will be stronger than when analyzed separately. I expected that PM 2.5 and PM 10 would also be strongly correlated and due to the effect that particulate matter has on the alveoli of lungs, I expect PM 2.5 to show the strongest association. Because of the catalytic relationship between heat, ozone and NOX and high temperatures of the SJV, I expected that NOX would reveal a weak association or an inverse relationship when compared to ozone. I anticipated that a combination of ozone, temperature, PM 2.5 and PM 10 will result in the highest model fit best explaining ARHR in SJV.

## METHODS

### Study Site Description

The study area boundary was the San Joaquin Valley of central California. This area covers 8,161 square miles and is surrounded by mountain ranges on the south, west and eastern edges (US. Census 2010). The climate of the region is characterized by extreme temperatures and heat waves in the dry summer months and mildly cold winters with very low rainfall. The San Joaquin Valley includes the following seven counties: Kern, Fresno, Kings, Merced, Maricopa, Stanislaus, San Joaquin, and Tulare. Kern County and Fresno County are the largest in populations. Air quality is unhealthy, and Kern and Fresno counties are consistently ranked in the top five counties with the worst air quality in the United States (State of the Air 2016). Interstate 5 and 15, are both major shipping routes connecting northern and southern California and connecting California to the well as the Eastern United. States. These routes run directly through the SJV counties, contributing

# Study Site Map

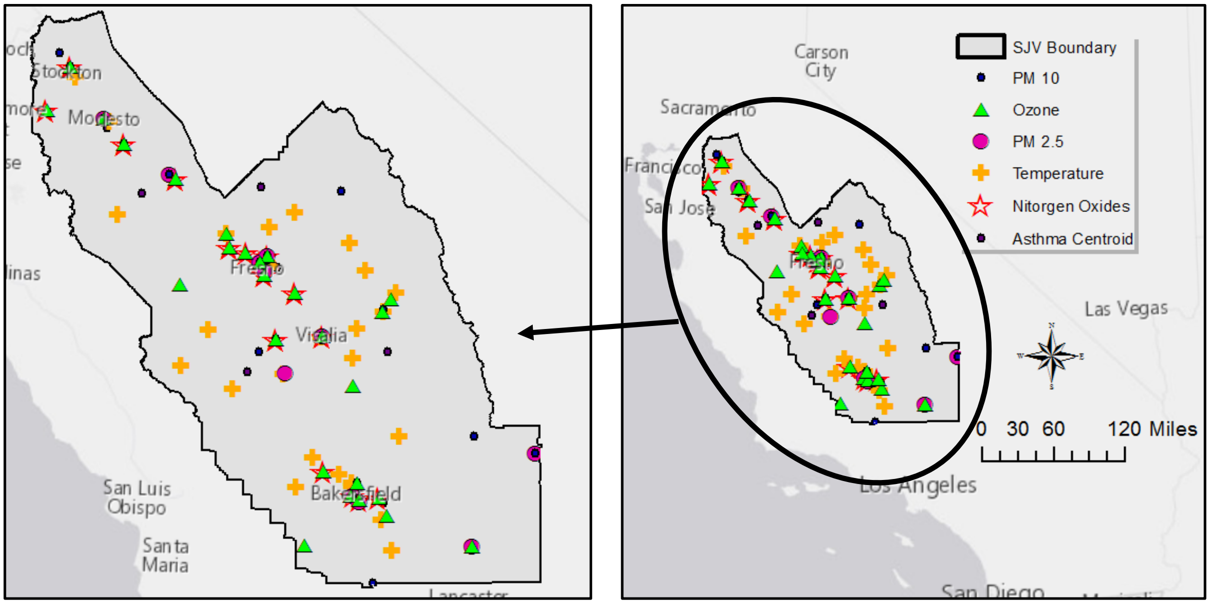


**Figure 1 Study Site of SJV.** (a) Showing the general location of SJV in California, major cities, geographic characteristics and interstates. The irregular distribution of air pollutant and temperature monitoring stations and county centroids is shown within the SJV boundary

vehicular and diesel emissions. Oil extraction and refineries are located throughout the valley contributing greater emissions. The total population of Kern County is 874,589 with 42% residing in the urban center Bakersfield. Asthma rates in Fresno and Kern Counties are some of the highest in California and the Nation (US. Census 2010). Approximately 12.6% of the population in Kern County suffers from asthma. (State of the Air 2016). ARHR is consistently higher in the valley's counties when compared to other counties and this trend is clearly apparent from 2011-2013 (State of the Air 2016). Fresno, Kern, Kings Merced and Stanislaus had the highest ARHR when compared to the neighboring counties. (see Figure 2). These same counties were ranked in the top 10 California counties with the highest number of days a year where ozone and particulate matter safety regulations are failed (State of the Air 2016). Median income across the SJV is approximately $48,552 falling $12, 542 below the average for California and 22.9% are living under the poverty line which is 7% above the average of California (US. Census 2010). Poverty in the SJV further exacerbates this health risk.

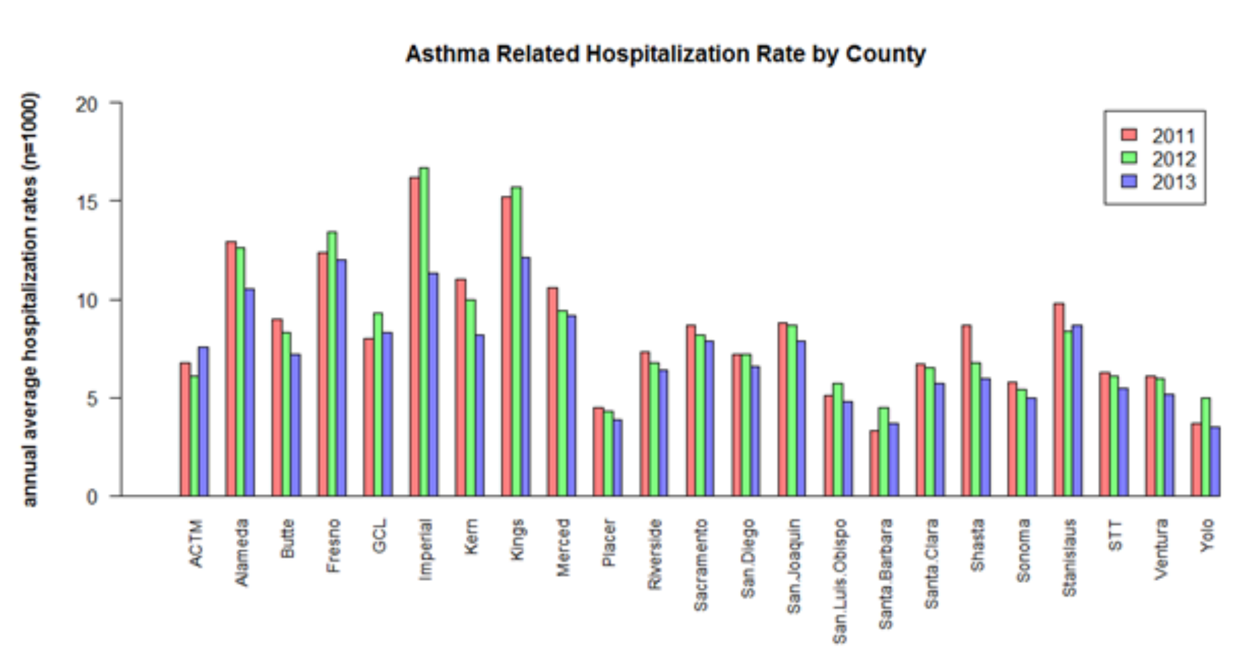


**Figure 2 Data on Asthma Related Hospitalization Rates for counties.** Rate data representing the number of people with asthma per 1000 population units. Counties in the SJV such as Kings, Kern, Merced, Stanislaus and Fresno show some of the highest hospitalization rates for the study period.

## Data Collection

Secondary data was collected and compiled into a database management system that supports an object oriented model compatible with ArcGIS software for efficient data collection and integration. The temporal scale analyzed covered 2011 through 2013. I collected data on annual average maximums for temperature, 8-hour ozone (ppm), 24- hour PM 2.5 (ug/m$^3$), 24-hour PM 10 (ug/m$^3$), 24-hour NOX (ppb) and ARHR, and integrated the data into a SJV Public Health Geodatabase (see Figure 3). Finding quality data posed a great challenge, as I used a variety of sources from local, statewide and national databases to meet the data requirements. Specifically, public health data was most difficult to find for the study period and I was restricted to only annual average data for hospitalization rates at the county level. Temperature, ozone, PM 2.5, PM 10 and NOX monitoring networks were created for each county of the San Joaquin Valley of California. The same monitoring network could not be used for each year because monitoring stations for temperature and air pollutants vary in number and distribution. Because monitoring is limited, I included monitoring stations and centroids in the counties immediately surrounding SJV to ensure enough points to justify interpolation. Coordinate data for each monitoring station was then joined to each station and I projected the points in ArcGIS. In this way I mapped each monitoring network. I calculated the centroid of each county in ArcGIS and extracted annual average ARHR for the study period thereby creating a point network for ARHR.

## Data Collection Model

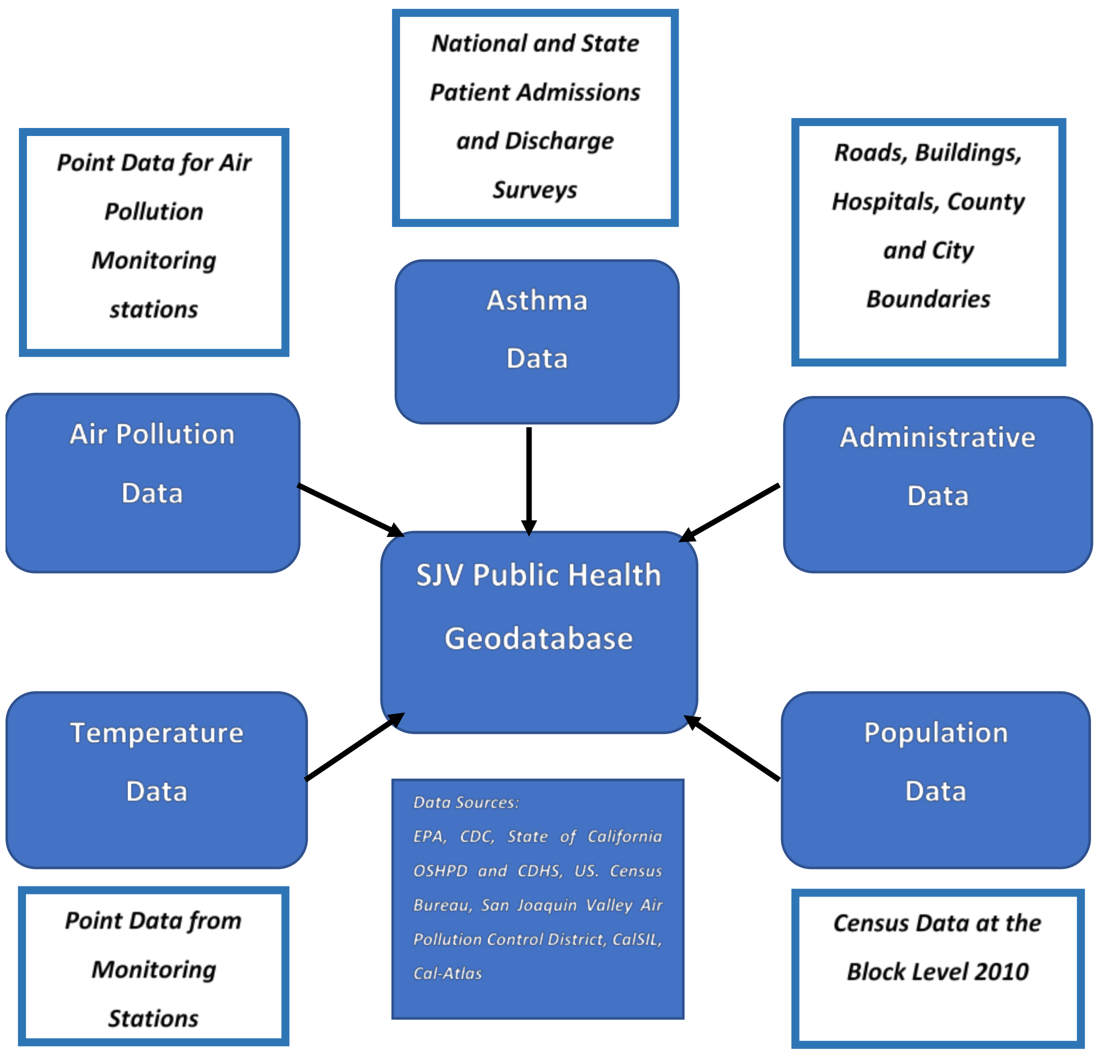


**Figure 3 Data Collection Model for SJV Geodatabase.** Conceptual model I followed for building a SJV Public Health Geodatabase with descriptions and sources of data.

**Geostatistical Analysis and Interpolation**

I conducted a preliminary data analysis for each monitoring network calculating summary statistics and creating bar plots to identify and better understand trends in the data (see Appendix A). I analyzed the spatial distribution of ozone, temperature, PM 2.5, PM 10, NOX and ARHR data in the geostatistical wizard within ArcGIS using a number of statistical tools creating histograms, semivariograms, and scatterplots to determine the distribution and trends in the data. Spatial autocorrelation was a concern because clustering in sample location and attribute value can lead to inaccuracy in later regression results (Gorai et al. 2014). A Spatial Autocorrelation (Global Moran's I) analysis was conducted for each variable for the period of the study. Global Moran's I works by testing if a distribution follows an expected random distribution as the null hypothesis; if a distribution is not random then the test will produce unusually high or low Moran's I statistic corresponding to a clustered or a dispersed distribution.

After analyzing the spatial distribution of the data, I determined that due to the irregular point distribution of the monitoring stations and centroids, Ordinary Kriging would be the optimal method of interpolation. Ordinary Kriging is an interpolation method that creates a smooth surface from irregularly spaced data points based on spatial variations and provides benefits in increased accuracy in the estimated surface when irregularities exist (Tobler. 1970). Not enough points were available for ARHR to justify Inverse Distance Weighting or Spline. This is consistent with the methodology used when analyzing public health and air pollution data found in foundational literature (Tobler. 1970). Ordinary Kriging also offers the option of applying a polynomial equation to remove trends found in the data. To ensure accuracy and consistency in the regression analysis, I interpolated all data using Ordinary Kriging. Continuous data layers were interpolated from point networks for temperature, ozone, ARHR, PM 2.5 and PM 10, NOX and I created spatial distribution maps for the study period. I determined the accuracy of the interpolation by analyzing the mean square error (MSE) and the root mean square standardized error (RMSSE). I determined the measure of fit for the interpolation model by comparing if the MSE was close to 0 and if the RMSSE was close to 1, and I used this as the measure for a successful interpolation.

**Table 1. Summary statistic for air pollutants, temperature, and ARHR.** Showing the mean, maximum, minimum and standard deviation for each study variable and year of the study. Variation is evident between each year.

| PARAMETER | MEAN | MAX | MIN | STANDARD DEV. | COUNT |
|---|---|---|---|---|---|
| **OZONE** | | | | | |
| **2013** | 0.0915 | 0.106 | 0.067 | 0.009183 | 26 |
| **2012** | 0.094556 | 0.116 | 0.033 | 0.014513 | 27 |
| **2011** | 0.091417 | 0.105 | 0.068 | 0.009115 | 24 |
| **TEMPERATURE** | | | | | |
| **2013** | 77.003525 | 85.73 | 55.581818 | 5.867315 | 30 |
| **2012** | 76.522566 | 85.211111 | 56.883333 | 5.814738 | 27 |
| **2011** | 77.80834 | 82.458111 | 67.278423 | 3.505061 | 30 |
| **ASTHMA** | | | | | |
| **2013** | 7.269565 | 12.1 | 3.5 | 2.495637 | 23 |
| **2012** | 8.308696 | 16.7 | 4.3 | 3.33309 | 23 |
| **2011** | 8.43913 | 16.2 | 3.3 | 3.339323 | 23 |
| **PM 2.5** | | | | | |
| **2013** | 11.870866 | 21.062393 | 5.52037 | 3.903083 | 30 |
| **2012** | 10.914517 | 36.8875 | 4.46 | 5.655766 | 32 |
| **2011** | 10.778588 | 18.207652 | 6.314321 | 3.417265 | 31 |
| **PM 10** | | | | | |
| **2013** | 27.178701 | 51.786885 | 13.275862 | 10.034988 | 47 |
| **2012** | 22.671609 | 43.066667 | 12.410714 | 7.41244 | 36 |
| **2011** | 22.448053 | 39.52459 | 11.428571 | 6.211438 | 39 |
| **NOX** | | | | | |
| **2013** | 16.000756 | 42.559973 | 0.290468 | 10.574816 | 52 |
| **2012** | 20.564551 | 42.261429 | 1.316527 | 10.297284 | 52 |
| **2011** | 20.903088 | 39.922222 | 1.525568 | 10.193887 | 50 |

## Analysis

Once each kriging model fit was found, I subjected the interpolations to regression analysis. Using the sampling tools in ArcMap 10.2.3, I took a random sample of 36 points over the study area; a weighted distance of 20,000 meters was used to ensure even sampling over the entire extent of the study area. I extracted data using the multi variable point extraction tool to infuse these points with ARHR, ozone, temperature, PM 2.5, PM 10 and NOX data for the study period. I now had data for each variable at a specific geographic location and regression analysis could be performed. Ozone, temperature, PM 2.5, PM 10 and NOX were held as the independent variables and ARHR was held as the dependent variable in all regression methods I tested. I restricted the analysis to regression methods using only a linear regression model because linear regression is the optimal method for measuring associations between continuous variables (Gorai, 2014). Using the correlation matrix tool in R-commander, I assessed the relative strength and direction of the relationships by creating a regression matrix (see Appendix D3 for correlation coefficients). This method works by running a two tailed Pearson correlation on every study variable producing a summary matrix of correlation coefficients (r-value) for each variable (Gorai, 2014). A correlation coefficient greater than or equal to 0.40 was the criteria for an association. A P-Value equal to or less than 0.05 was the criteria for significance.

Next, to assess the strength of each relationship, I conducted three separate linear regression methods in the following order: linear regression, OLS and GWR. Linear regression works by calculating a straight line that best-fits the values of a linear function, plotted on a scatter graph as data points. (ESRI, 2011). I used linear regression to assess the associations without regards to spatial relationships using a random sample over the entire study area. I used to assess the general relationship and significance and helped to build a set of explanatory variables that have the highest fit followed by GWR. GWR works by creating a local model fitting a linear regression equation to every feature in the dataset; GWR constructs these separate equations by incorporating the dependent and explanatory variables of features falling within a specific weighted distance of each target feature (ESRI, 2011). GWR was used to assess the local and global relationship between the variables and ARHR while taking into account spatial location as a weighted part of the correlation equation. This consideration of local relationships is a key benefit of using GWR because differences in local and global relationships can be identified (Gorai, 2014). Starting with an analysis of temperature ozone and ARHR, I used each regression method to assess the bivariate and multivariate relationships to determine if projected temperature rises and ozone penalty in SJV are a concern. I then tested nitrogen dioxide, PM 2.5 and PM 10 for association using these three regression techniques. To determine strength of association, I analyzed the coefficient of determination ($R^2$ value) to compare the measure of fit for each variable. I chose a value greater than or equal to 0.40 as the measure for a strong association and a P-Value equal to or less than 0.05 was the criteria for significance for the linear regression, OLS and GWR.

Once the relationship for each variable was well understood from the results of the OLS, GWR, regression matrix and linear regression, I identified which of the five explanatory variables were found to show a positive association with ARHR. These air pollutants became the focus of the explanatory regression model to verify if the model fit could be improved by multivariate analysis. First, I conducted a multivariate analysis using linear regression to better understand how these variables are related to ARHR. Next these air pollutants were analyzed using OLS and GWR to assess the local and global spatial relationship these variables have with ARHR. To determine the completeness of the model, I ran a spatial autocorrelation (Global Moran's I) test on the residuals produced by the GWR. The residuals measure the difference between predicted and observed values. Clustering of residuals indicate a model that has been specified wrong which is characterized by high local variation in error. If residuals are found to be distributed randomly than this indicates the model is specified correctly and therefore entails another criterion to assess the accuracy of the explanatory model.

## RESULTS

### Spatial Distributions

When assessing the results of the test for spatialautocorrelation, I found NOX, PM 2.5 and PM 10 produced a positive Moran's I statistic with a significant P-Value indicating a clustered distribution in the spatial network (see Appendix B). I found temperature and ARHR were distributed randomly producing a test statistic close to the expected 0 with an insignificant P-value. I found ozone was distributed randomly in 2011 and 2013, but in 2012 ozone followed a dispersed trend. Trends were removed for NOX, PM 10 and PM 2.5 by using a second order de-trending equation before preforming kriging; I found this improved the model fit and the accuracy of the predicted surface when compared to interpolations without trend removal. I created spatial distribution maps for the study period showing the spatial variation of each variable across the SJV (see Figure 3 and Appendix B). I found all interpolations had a stable model fit producing MSE values close to 0 and RMSSE values close to 1 indicating a reasonably accurate interpolation with little over estimation in the predicted surface (see Appendix B).

# Spatial Distribution Maps (SJV)

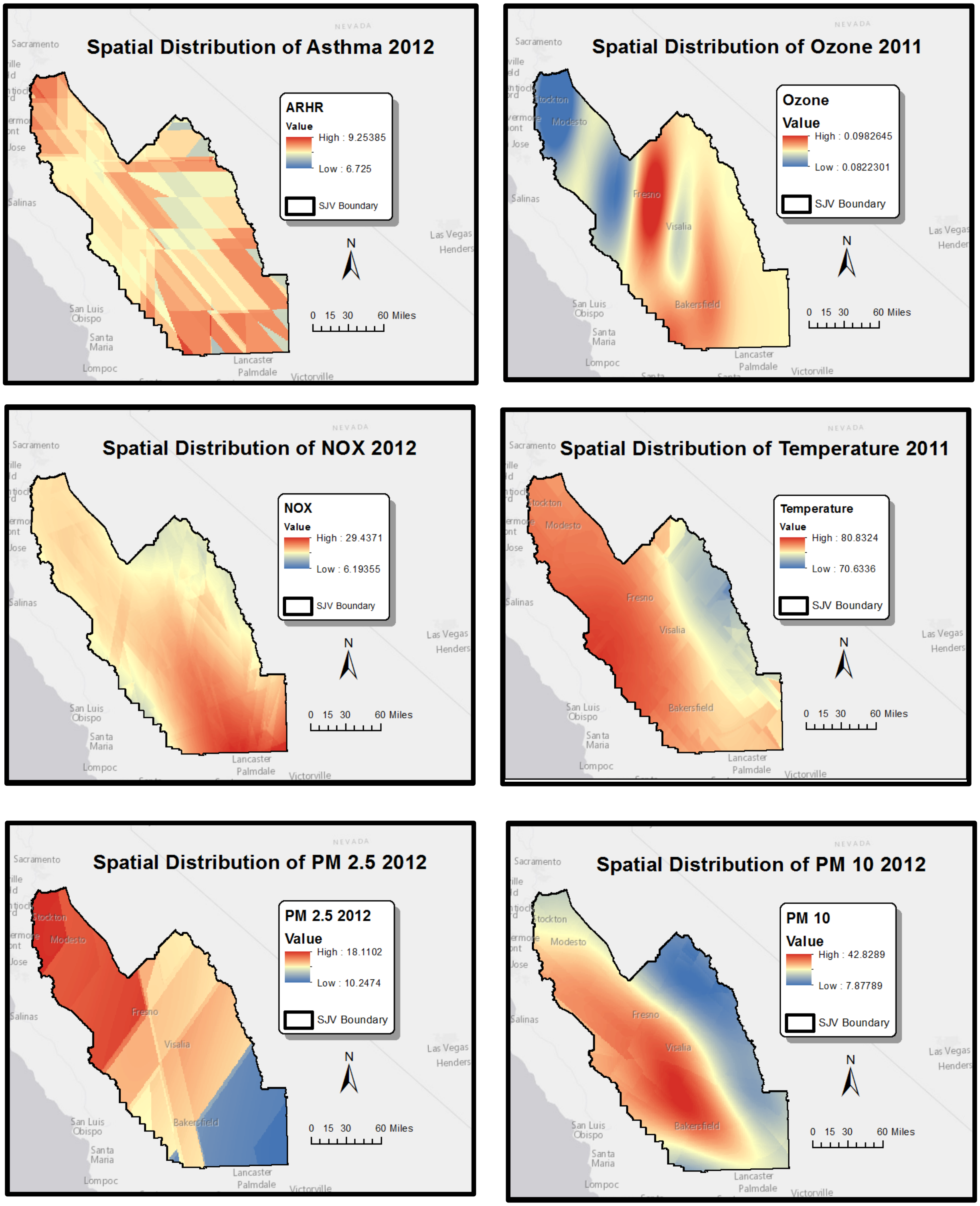


**Figure 4. Spatial Distribution Maps.** Showing average annual maximum ozone concentration (ppm), average annual maximum temperature, average annual $NO_2$, average annual PM2.5, average annual PM10 and average annual ARHR over SJV for the year 2012.

**Regression Results**

For temperature and ozone, I found that the correlation coefficient ranged from r-value of -0.10596 to 0.21148 and -0.04780 to 0,10815 indicating no association for either variable over the study period (see Appendix D3 for correlation coefficient values). I found that PM 2.5 was most associated with ARHR with r-value of 0.83288 for 2012 and for 2012 but a weak negative association for 2013. PM 10 followed an identical trend in r-value but the associations were much weaker than associations for PM 2.5. I found associations ranging from -0.15037 to 0.5944 for the study period (see Appendix D3 for correlation coefficient values). When looking at $NO_x$, I found a strong negative relationship with ARHR producing an r-value of -0.78696 for 2012 but weakly associated 2011 and 2013 with r-value of -0.19325 and 0.1903 (see Appendix D3 for correlation coefficient values). The results of the correlation matrix values are displayed showing correlation coefficient for each scenario tested (see figure 5).

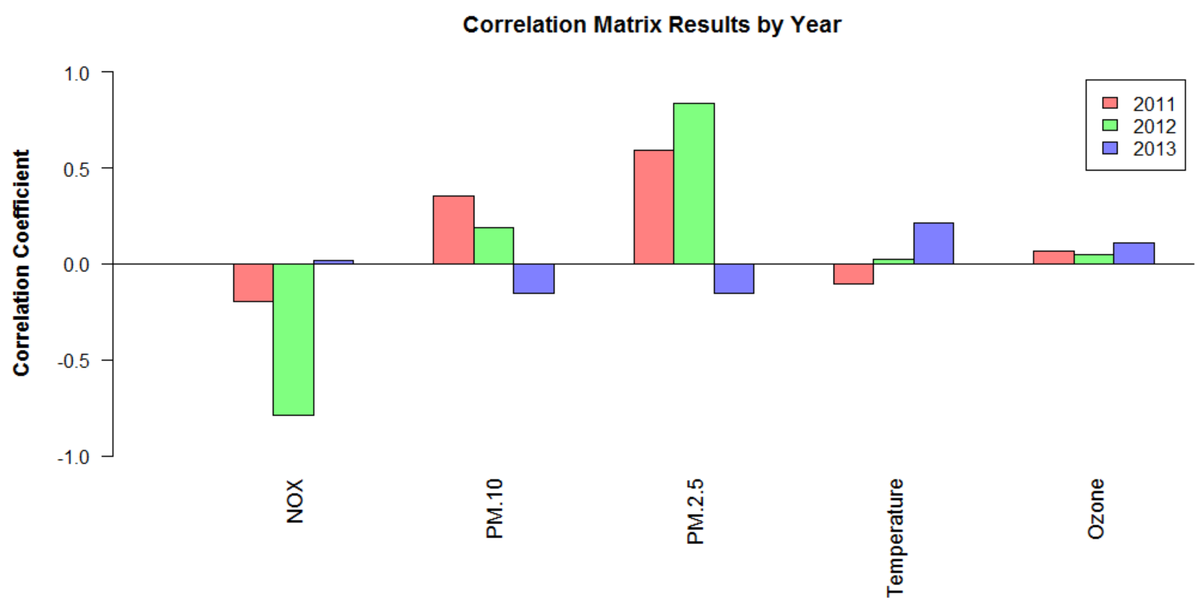


**Figure 5. Correlation matrix results showing strength and direction of association.** Bar graph showing the strength and direction of the correlation coefficient. The correlation coefficient

When using linear regression, I found that the results followed similar trends as the correlation matrix. Temperature and ozone were not positively correlated with ARHR with a low

$R^2$ values ranging from -0.1700 to 0.02709 for linear regression and for GWR thought these high values were found to be highly insignificant (see Appendix D for $R^2$ values). I again found temperature to show no association $R^2$ values ranging from -0.2674 to 0.16630 for linear regression and for GWR (see Appendix D for $R^2$ values). The multivariate analysis did not improve the model fit, showing no association. I found $NO_x$ was associated with a $R^2$ value of 0.60810 for linear regression solidifying the strength of the negative association found in the correlation matrix but no significant associations were found using GWR (see figure 5 and 7). PM 2.5 was most associated with ARHR with a $R^2$ value of 0.8188 using GWR and 0.68700 for 2012 (see figure 7-9). I found PM 2.5 was associated using GWR with an $R^2$ value of 0.8378 for 2011 and a weaker association of 0.33430 using linear regression (see figure 7-9). I found PM 10 to have an association with ARHR with a $R^2$ value of 0.8068 when using GWR and 0.764800 when using linear regression for 2012 and no associations for any method for 2011 (see figure 7-9). I found no significant results for either PM 2.5 or PM 10 for 2013.

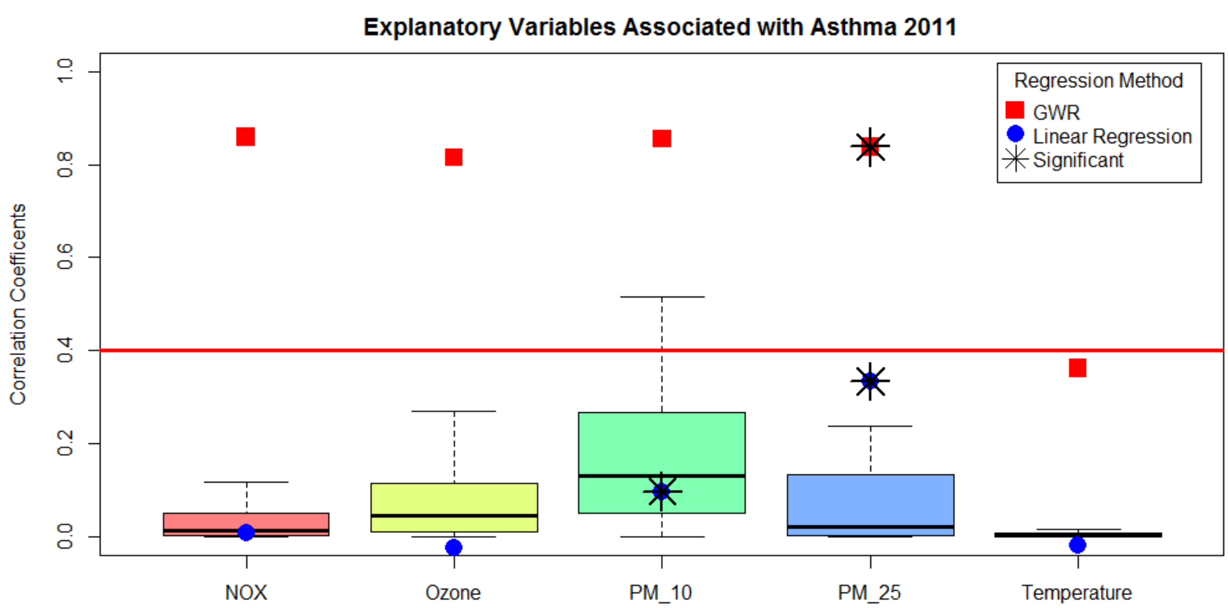


**Figure 6. Distribution of measure fit for all variables and ARHR.** Local $R^2$ values are shown in the boxplot with the global GWR and linear regression results plotted for comparison for each variables relationship with ARHR. PM 2.5 shows a strong association for GWR and weaker association for the linear regression.

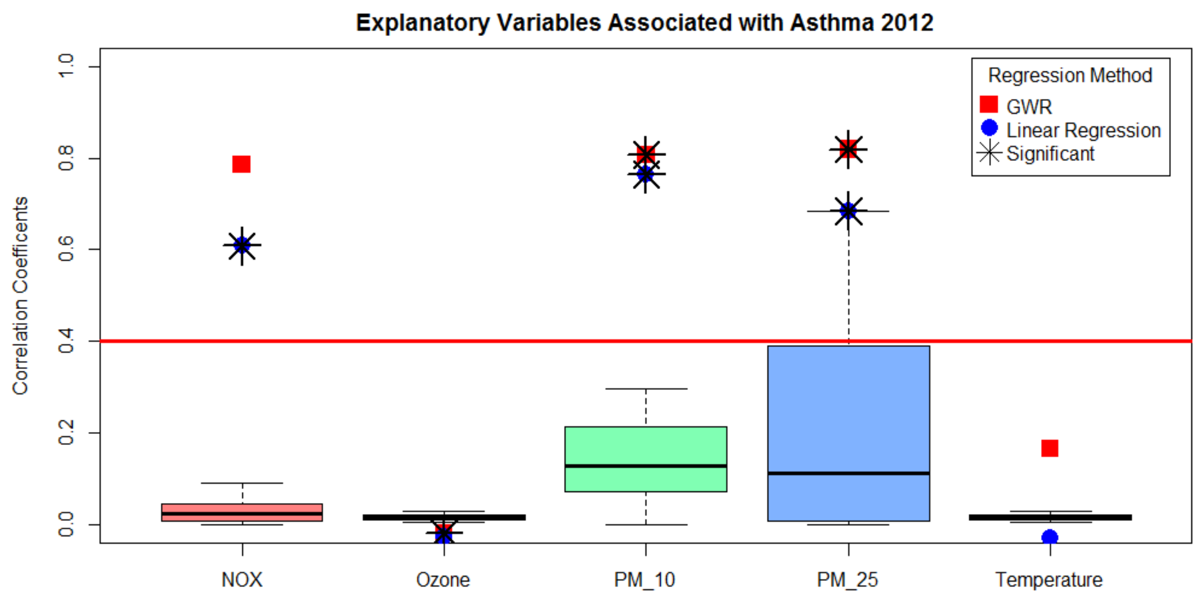


**Figure 7. Distribution of measure fit for all variables and ARHR:** Local $R^2$ values are shown in the boxplot with the global GWR and linear regression result plotted for comparison for each variables relationship with ARHR. No significant associations are observed for any variable ARHR. The adjusted $R^2$ value was the measure for how well the model explained ARHR.

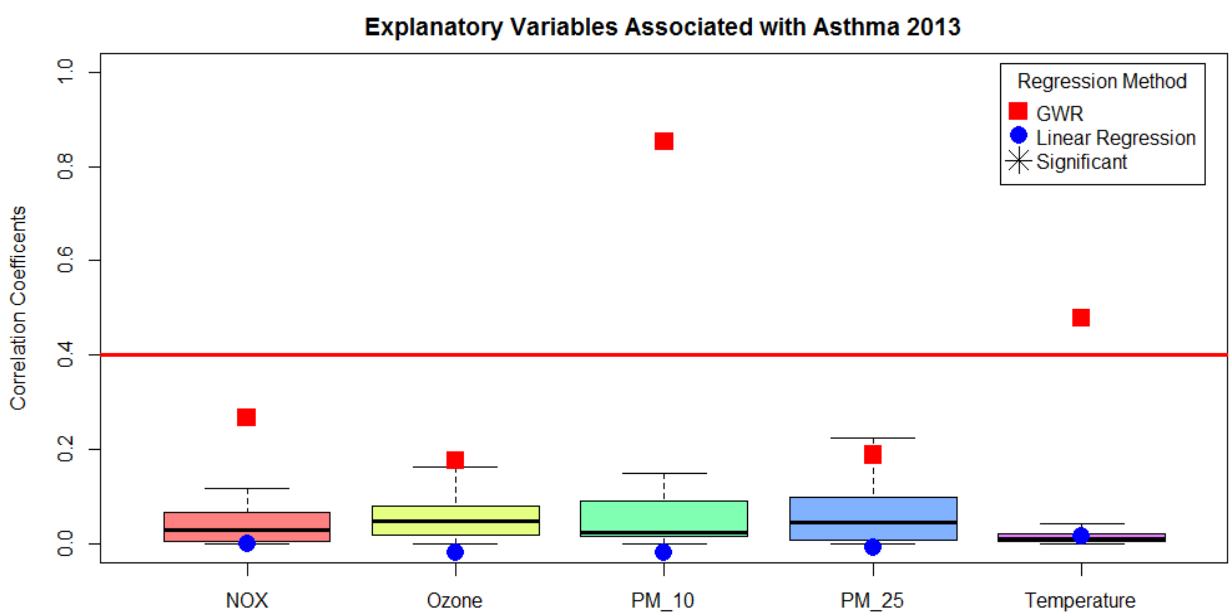


**Figure 8. Distribution of measure fit for all variables and ARHR**: Local $R^2$ values are shown in the boxplot with the global GWR and linear regression result plotted for comparison for each variables relationship with ARHR. PM 2.5 and PM 10 both show a strong association for GWR and linear regression. Ozone shows a weak significant association for GWR and NOX shows a strong association for linear regression The adjusted $R^2$ value was the measure for how well the model explained ARHR

**Summary of Significance**

The results of my analysis suggest no positive association between ozone, temperature and ARHR for the study period. However, a weak association was found for the 2012 year between ozone and ARHR (see figure 7). The multivariate analysis of temperature, ozone and ARHR yielded no significant results. When looking at $NO_x$ and ARHR, I found a significant negative association for 2012. PM 2.5 and PM 10 were found to be positively correlated with ARHR for 2012 with an $R^2$ value of 0.6776 for the linear regression model and the model fit was increased to 0.7666 using GWR (see figure 9). The results of the linear regression and GWR are displayed as boxplots showing measure of fit for each scenario tested and distribution of local $R^2$ values to compare global and local relationships (see figure 6-9). I found that the mean of the local $R^2$ value was lower than the global $R^2$ value for GWR across the study period (see figure 6-8). Linear regression showed similar measures of fit with significance as the global measure of fit for GWR over the study period. PM 2.5 and PM 10 show a strong association for linear regression and GWR indicating a good model fit at the global level but less at the local level shown by the lower mean of local $R^2$ value. To assess the accuracy of the results, I compared both P-Values and Moran's I test statistics of the residuals of the GWR and found all significant results had random residuals and none were clustered (see Appendix E3 for test statistics and P-Values).

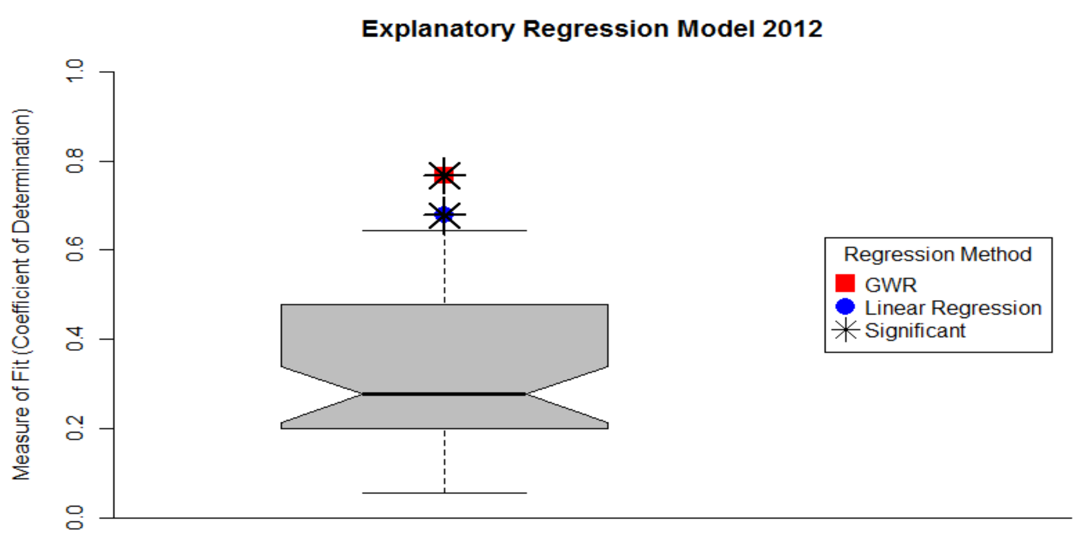


**Figure 9. Distribution of measure fit for Explanatory Regression Model**: Local $R^2$ values are shown in the boxplot with the global GWR and linear regression result plotted for comparison. The adjusted $R^2$ value was used as the criteria for how well the model explained ARHR. PM 2.5 and PM 10 show a strong association for linear regression and GWR indicating a good model fit at the global level but less at the local level shown by the lower mean of local $R^2$ . This local mean however was the highest for the study ranging from weak to

# DISCUSSION

Understanding how air pollution is associated with asthma related hospitalizations (ARHR) is vital to understanding the public health risks and needs of sensitive populations in the San Joaquin Valley (SJV). Geographic information systems (GIS) provide a geostatistical platform for analyzing air pollutants, and are useful tools for assessing public health and air pollution data efficiently to better understand this complex spatial problem of how air pollution effects sensitive populations with asthma. Contrary to my expectations, when analyzed together temperature and ozone appear to have a weak association with ARHR across all regression methods and study years. Temperature was also not found to be associated with ARHR and when analyzed together, ozone and temperature were insufficient in explaining ARHR. NOX was expected to be associated with ARHR, but I found only a negative association yielding a significant result across two methods for the year 2012. The most important finding from the regression analysis of air pollutants and ARHR was for the year 2011 and 2012 between PM 2.5 ARHR. I found that of the six regression techniques tested, five yielded significant associations. I found the optimal explanatory model was between PM 2.5 and PM 10 using both linear regression and GWR. No significant results were found for any explanatory variables for the year 2013.

## Interpretation

Opposing my anticipated results, temperature and ozone do not have a more significant association with ARHR when analyzed together, rather than discretely, and I found a weak association with ARHR. I found no positive association between ozone and ARHR, contradicting my predicted results and this was consistent across each study year and regression methodology tested. I did not identify a positive association between temperature and ARHR and this lack of association was consistent across all regression methods tested. From my results the catalytic relationship between temperature and ozone and projected temperature rise over the SJV do not appear to be significant public health threats. Thus, efforts to reduce other pollutants and triggers of asthma attacks may yield a better use of resources in Kern County and other counties in SJV.

Even though temperature and ozone may not be strongly associated with asthma attacks, this catalytic relationship is still a concern for the health of sensitive populations in the SJV area because of known respiratory stress caused by ozone pollution. It is vital to act as quickly as possible in reducing emissions from fossil fuels and precursor emissions of ozone to avoid the possible externalities associated with the projected temperature rise and subsequent rise in ozone concentrations over the San Joaquin Valley.

As I expected as a possible result, NOX was found to exhibit an inverse relationship with ARHR for the year 2012. However, this finding was not consistent and a negative association was not found for the years 2011 and 2013. From my results, NOX is not a significant risk for ARHR. As I had expected, the most significant finding from the regression analysis of air pollutants and ARHR was between PM 2.5 and ARHR; I found that five of the six regression methods tested resulted in a robust model fit. When analyzing PM 10, I found this pollutant resulted in a robust model fit for three of the six regression methods tested, PM 10 followed a similar trend as PM 2.5 as I had expected but did not explain ARHR as robustly as PM 2.5

I found that PM 2.5 and PM 10 together were associated with ARHR and produced the optimal explanatory model for explaining ARHR in SJV. Geographically Weighted Regression (GWR) improved the fit of the regression model. This is consistent with Gorai et al. (2014) study using the same methodology and finding a strong association with PM 2.5 and ARHR using linear regression and GWR. From my results, PM 2.5 and PM 10 are a significant risk to ARHR and targeting these pollutants emissions sources offers protection to sensitive populations with asthma. These results suggest that efforts to pinpoint and reduce PM 2.5 and PM 10 may be a better approach to reducing asthma related hospitalizations in SJV than only focusing on a single pollutant and source. A more holistic approach to emissions reduction is an effective solution. Because NOX emissions are a precursor to ozone formation, reducing sources of NOX emissions would reduce both these pollutants solving two problems with one solution and mitigating possible associations and risks not captured in my study design. Particulate matter and nitrogen oxides are sourced predominantly from vehicular emissions along transportation routes in the SJV. Continuing and ramping up efforts in reducing vehicular emissions is recommended as an ideal solution to mitigate the emissions of all three pollutants and in turn reducing risk to sensitive populations with asthma immediately.

**Limitation**

When using a GIS system to analyze public health data, I encountered limitations in accuracy of the geostatistical analysis due to the irregularity in the air pollution and temperature monitoring networks. Because monitoring is limited, data was interpolated and these estimated surfaces exhibited error between actual and predicted values. The spatial distribution of monitoring stations across SJV is not uniform, resulting in error in the predicted surface. Inaccuracy also can propagate from the instruments themselves and quality of the data collected by monitoring stations may be more limited in specific spatial locations. Another limitation is the accuracy of the health data I compiled as asthma sufferers also may see a private provider, and thus, the ARHR rate may be reported lower than what is actually observed in some locations. Also because heath data was not readily available, annual averages were used and I did not include daily or monthly values as a major component of the analysis. A study considering the lag time between days of high ozone and temperature and the day the asthma hospitalization occurred may shed light on the risk the climate penalty has in exacerbating the asthma problem in SJV. Because ozone pollution is known to be most problematic in the summer months and particulate matter is most problematic during the winter months, restricting the analysis to a monthly or daily basis rather than using annual averages may yield a finer-grained, more accurate regression model and better associations for these air pollutants and ARHR.

**Future Direction**

The next step in understanding how air pollution and temperature affects asthma would be to explore the associations using alternative regression models within ArcGIS to better understand how these pollutants and climate factors affect public health in the SJV on a local level and globally for California. Because secondary data was collected and processed into geodatabase within a GIS system for this study, a platform is now available for spatial-statistical analysis and can be used in future studies or combined with other explanatory variables and incorporation of climate models scenarios. Repeating the analysis using monthly and daily maximum data may yield a more robust model fit. By adding additional explanatory variables such as income, demographics, obesity and other air pollutants such as pesticides used in the area, a better model fit may be obtained explaining ARHR in SJV. Other spatial analysis techniques such as using buffering of pollution sources located in close proximity to populations with asthma could also shed light on the relationship.

**Broader Significance**

Understanding how projected increases in temperature will affect respiratory health is an essential part of understanding the risk to public health these environmental changes pose. Because I did not find an increased association between both high temperature and ozone levels on ARHR, projected temperature rise and corresponding increase in maximum ozone concentrations may not be a risk in directly causing a greater number of asthma attacks when both are at maximums. However, the climate penalty may still be a concern as the study design may have limited the results. Restricting the study to the ozone season summer months may improve these associations. Even though maximum temperature was not found to be associated, projected temperature rises may affect asthma sufferers indirectly by increasing the number of high ozone days over the summer months and the effect of ozone on respiratory airways. Mitigation efforts have the potential to abate this respiratory risk by reducing maximum concentrations PM 2.5 and PM 10 which I found to best explain ARHR in SJV. To be most effective in protecting populations with asthma, an effort to pinpoint and reduce PM 2.5 and PM 10 pollution sources is vital to mitigating ARHR. By linking the effects of air pollution to ARHR, my study findings support arguments pointing to the urgency of implementing policy and preventative measures to reduce air pollution and alleviate these pollution levels, in turn protecting the lungs of sensitive populations with asthma.

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# Appendix A: Data for Monitoring Stations

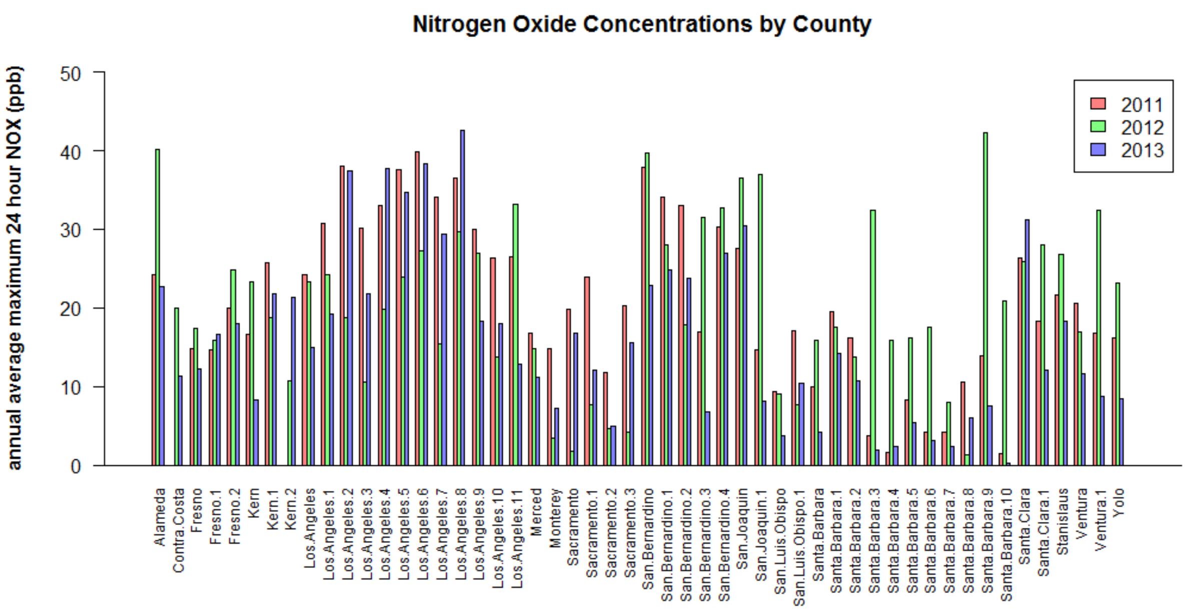
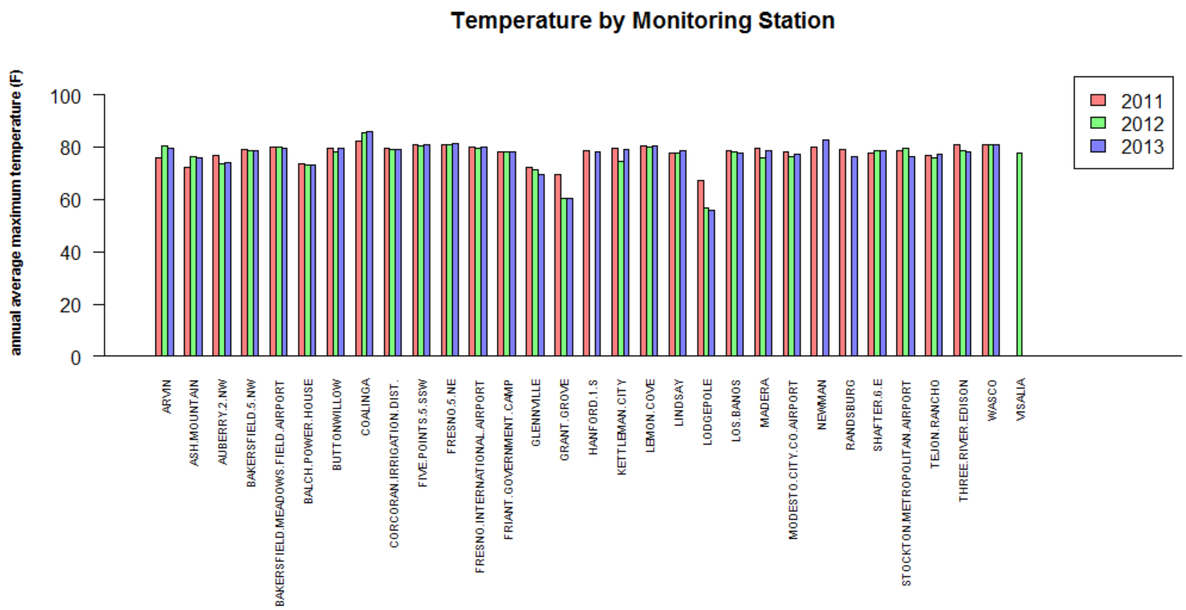



**Figure A1. Data on NOX for monitoring stations in by county.** Bar plots of average annual maximum 24-hour concentrations of PM 10 measured in parts per billion (ppb) and displayed by color for each year of the study period.



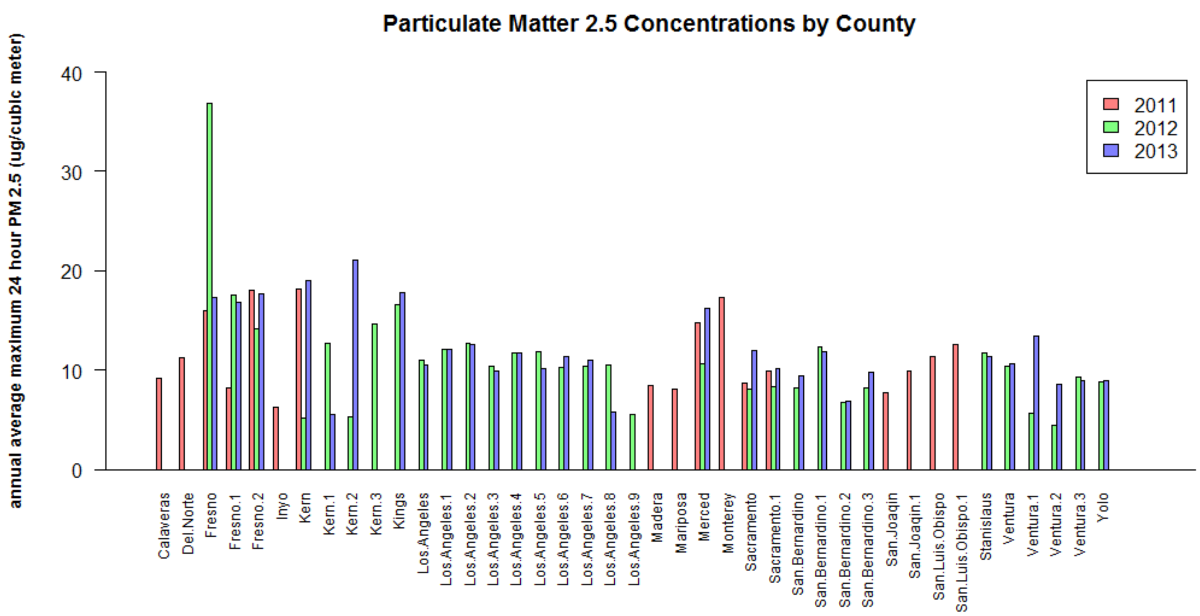




**Figure A3. Data on PM 2.5 for monitoring stations by each county.** Bar plots of average annual maximum 24-hour concentrations of PM 2.5 measured in micrograms per meter squared and displayed by color for each year

**Figure A2. Data on temperature by monitoring stations.** Bar plots of average annual maximum temperature measured in degrees Fahrenheit (F) and displayed by color for each year of the study period.

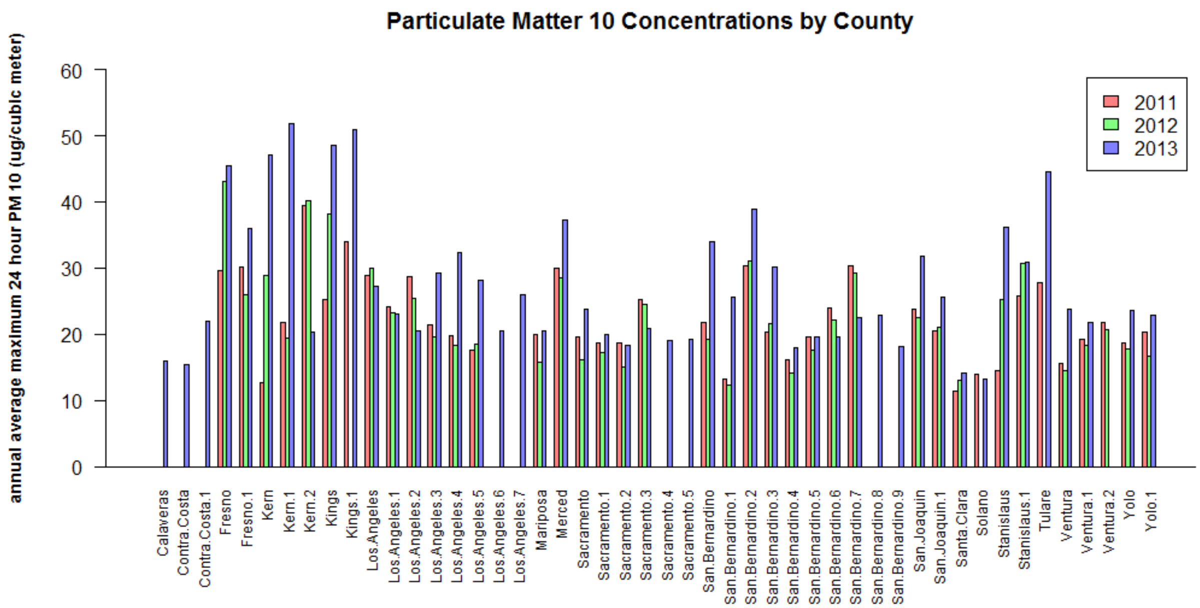



**Figure A4. Data on PM 10 for monitoring stations by each county.** Bar plots of average annual maximum 24-hour concentrations of PM 10 measured in micrograms per meter squared and displayed by color for each year of the study period.

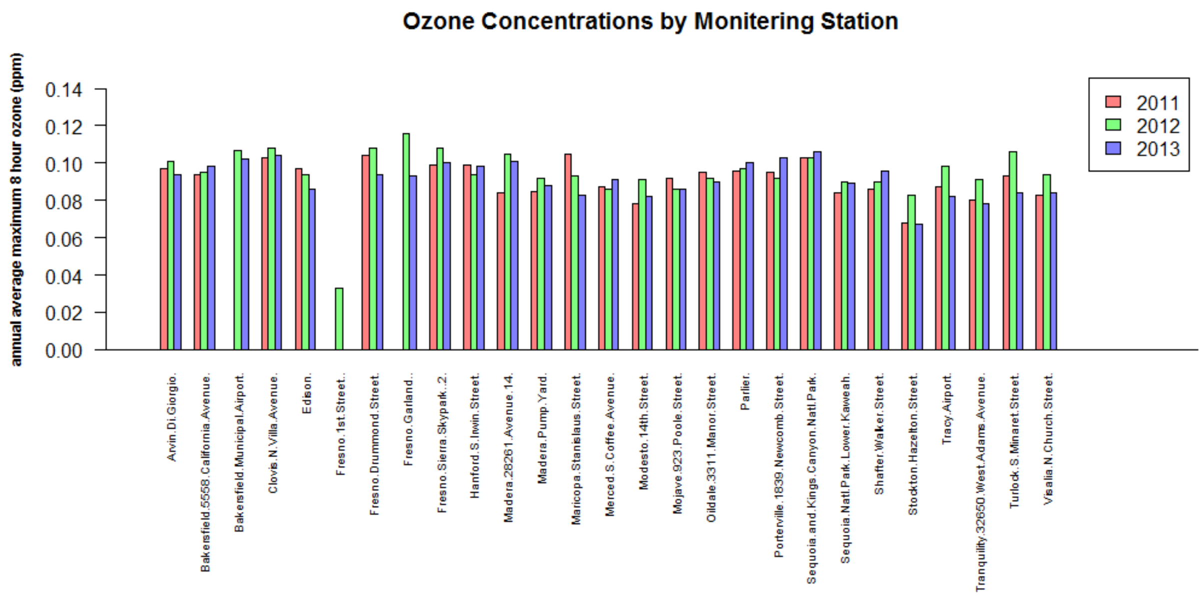



**Figure A5. Data on ozone for monitoring stations.** Bar plots of average annual maximum 8-hour concentrations of ozone measured in parts per million (ppm) and displayed by color for each year of the study period.

# Appendix B: Moran's I Test and Parameters for Interpolations

**Table B1. Results of the test for spatial autocorrelation (Global Moran's I) on monitoring networks.** Showing the Moran's, I statistic size and significance of p-value. A large negative Moran's I statistics indicate dispersion in distribution and a positive statistic indicate clustering and possible spatialautocorrelation in the distribution. The order of the trend indicates the type distribution and order of trend removal equation.

| PARAMETER | EXPECTED I | MORAN'S I | Z-SCORE | VARIANCE | P-VALUE | DISTRIBUTION | ORDER |
|---|---|---|---|---|---|---|---|
| **OZONE** | | | | | | | |
| **2013** | -0.04 | 0.161415 | 1.540934 | 0.017085 | 0.123333 | Random | None |
| **2012** | -0.038462 | -2.85678 | -8.557797 | 0.108457 | 0 | Dispersed | Second |
| **2011** | -0.043478 | 0.132897 | 1.258481 | 0.19642 | 0.208218 | Random | None |
| **TEMPERATURE** | | | | | | | |
| **2013** | -0.034483 | 0.160976 | 1.395175 | 0.019627 | 0.162963 | Random | None |
| **2012** | -0.038462 | 0.256248 | 1.464087 | 0.040519 | 0.14317 | Random | None |
| **2011** | -0.034483 | 0.142391 | 1.165446 | 0.023033 | 0.243839 | Random | None |
| **ASTHMA** | | | | | | | |
| **2013** | -0.045455 | -0.048939 | -0.047364 | 0.005413 | 0.962223 | Random | None |
| **2012** | -0.045455 | -0.076077 | -0.424965 | 0.005192 | 0.670862 | Random | None |
| **2011** | -0.045455 | -0.037329 | 0.911186 | 0.005307 | 0.911186 | Random | None |
| **PM 2.5** | | | | | | | |
| **2013** | -0.034483 | 0.557649 | 4.118252 | 0.020673 | 0.000038 | Clustered | Second |
| **2012** | -0.032258 | 0.394472 | 3.851982 | 0.012273 | 0.000117 | Clustered | Second |
| **2011** | -0.033333 | 0.186981 | 2.975908 | 0.005481 | 0.002921 | Clustered | Second |
| **PM 10** | | | | | | | |
| **2013** | -0.021739 | 0.439777 | 4.579146 | 0.010158 | 0.000005 | Clustered | Second |
| **2012** | -0.028571 | 0.307112 | 2.477923 | 0.018352 | 0.013215 | Clustered | Second |
| **2011** | -0.026316 | 0.162904 | 1.5603 | 0.014707 | 0.118689 | Random | None |
| **NOX** | | | | | | | |
| **2013** | -0.019608 | 0.804183 | 10.533758 | 0.006116 | 0 | Clustered | Second |
| **2012** | -0.019608 | 0.916089 | 11.550399 | 0.006563 | 0 | Clustered | Second |
| **2011** | -0.020408 | 1.009581 | 12.882175 | 0.006393 | 0 | Clustered | Second |

| PARAMETER | MODEL FIT | NUGGET | PARTIAL SILL | LAG SIZE | RANGE | MSE | RMSSE |
|---|---|---|---|---|---|---|---|
| **OZONE** | | | | | | | |
| **2013** | Stable | 0.667741 | 0.332259 | 0.208488 | 2.344792 | 0.098168 | 0.968034 |
| **2012** | Stable | 0.027787 | 0.000000 | 0.367059 | 4.388471 | 0.027787 | 1.008809 |
| **2011** | Stable | 0.646057 | 0.353943 | 0.110988 | 1.331861 | 0.061679 | 0.957083 |
| **TEMPERATURE** | | | | | | | |
| **2013** | Stable | 0.000000 | 36.604271 | 0.052645 | 0.456503 | 0.000803 | 0.862362 |
| **2012** | Stable | 0.000000 | 27.107988 | 0.066448 | 0.797377 | 0.059515 | 0.968287 |
| **2011** | Stable | 10.205757 | 4.666895 | 0.166440 | 1.465662 | 0.007100 | 0.872180 |
| **ASTHMA** | | | | | | | |
| **2013** | Stable | 9.001198 | 3.258544 | 0.030659 | 3.679078 | 0.000362 | 0.994298 |
| **2012** | Stable | 19.279921 | 0.000000 | 0.462695 | 5.552334 | 0.014545 | 1.013023 |
| **2011** | Stable | 19.719286 | 0.000000 | 0.462695 | 5.552334 | 0.012177 | 1.013908 |
| **PM 2.5** | | | | | | | |
| **2013** | Stable | 0.337206 | 0.398737 | 0.349155 | 4.189855 | 0.028307 | 0.880683 |
| **2012** | Stable | 71.505677 | 2.191315 | 0.370981 | 4.451772 | 0.080303 | 0.987972 |
| **2011** | Stable | 0.000000 | 16.142097 | 0.801110 | 1.652893 | 0.064860 | 0.997528 |
| **PM 10** | | | | | | | |
| **2013** | Stable | 0.764023 | 0.235979 | 0.764023 | 2.791929 | 0.070387 | 1.089957 |
| **2012** | Stable | 12.732700 | 131.423290 | 0.164334 | 1.397201 | 0.088269 | 0.876638 |
| **2011** | Stable | 0.866779 | 0.133221 | 0.186588 | 1.502630 | 0.015234 | 0.994199 |
| **NOX** | | | | | | | |
| **2013** | Stable | 44.754445 | 5.181701 | 0.307049 | 3.684593 | 0.001891 | 0.992264 |
| **2012** | Stable | 45.313844 | 0.844615 | 0.307049 | 3.684593 | 0.095086 | 0.967695 |
| **2011** | Stable | 0.000000 | 26.662772 | 0.306174 | 3.674092 | -0.049961 | 1.046354 |

# Appendix C: Spatial Distribution Maps 2011 and 2013 and Extracted Sample Data

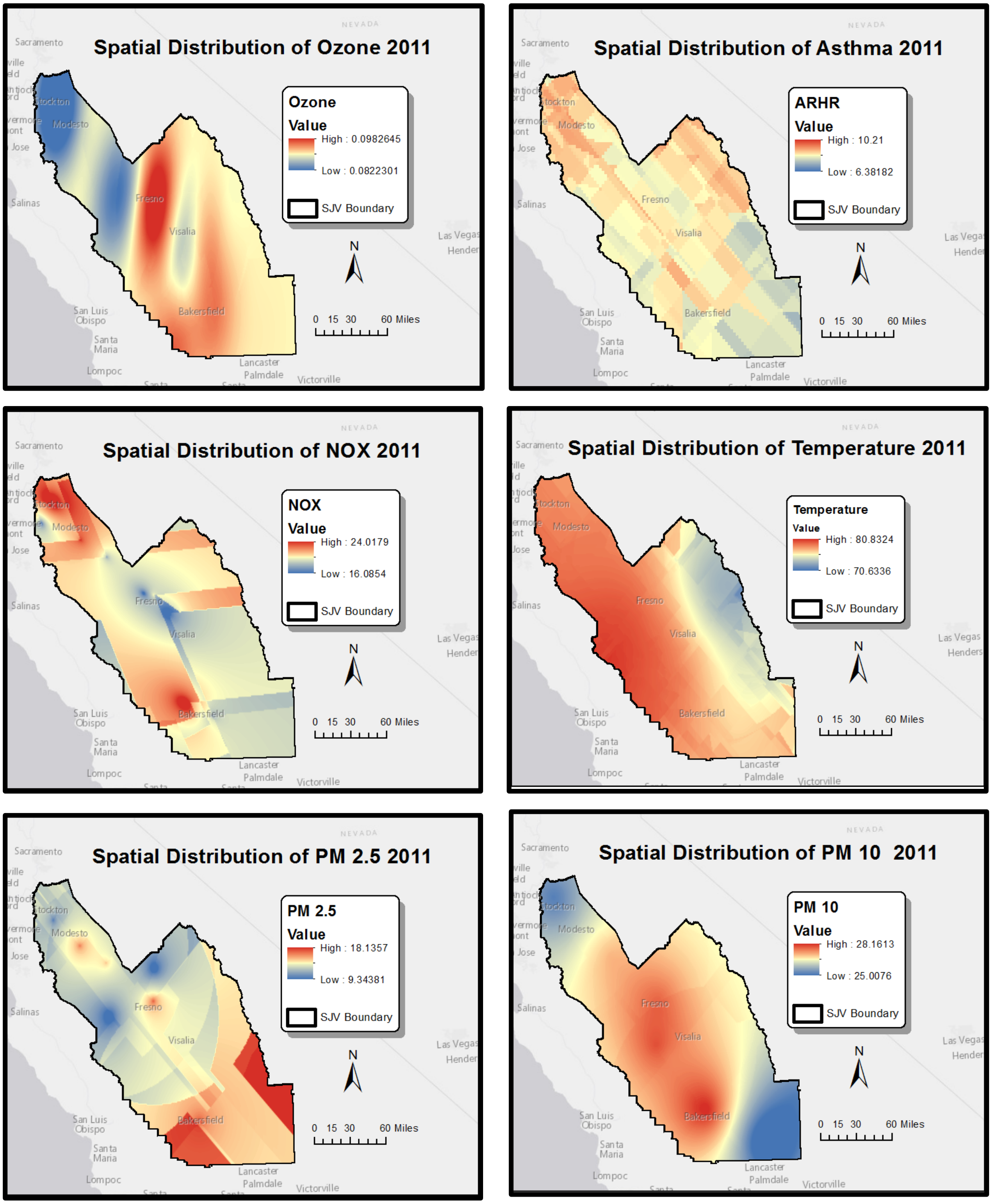



**Figure C1. Spatial Distribution Maps.** Showing average annual maximum ozone concentration (ppm), average annual maximum temperature, average annual $NO_2$, average annual PM2.5, average annual PM10 and average annual ARHR over SJV for the year 2011.

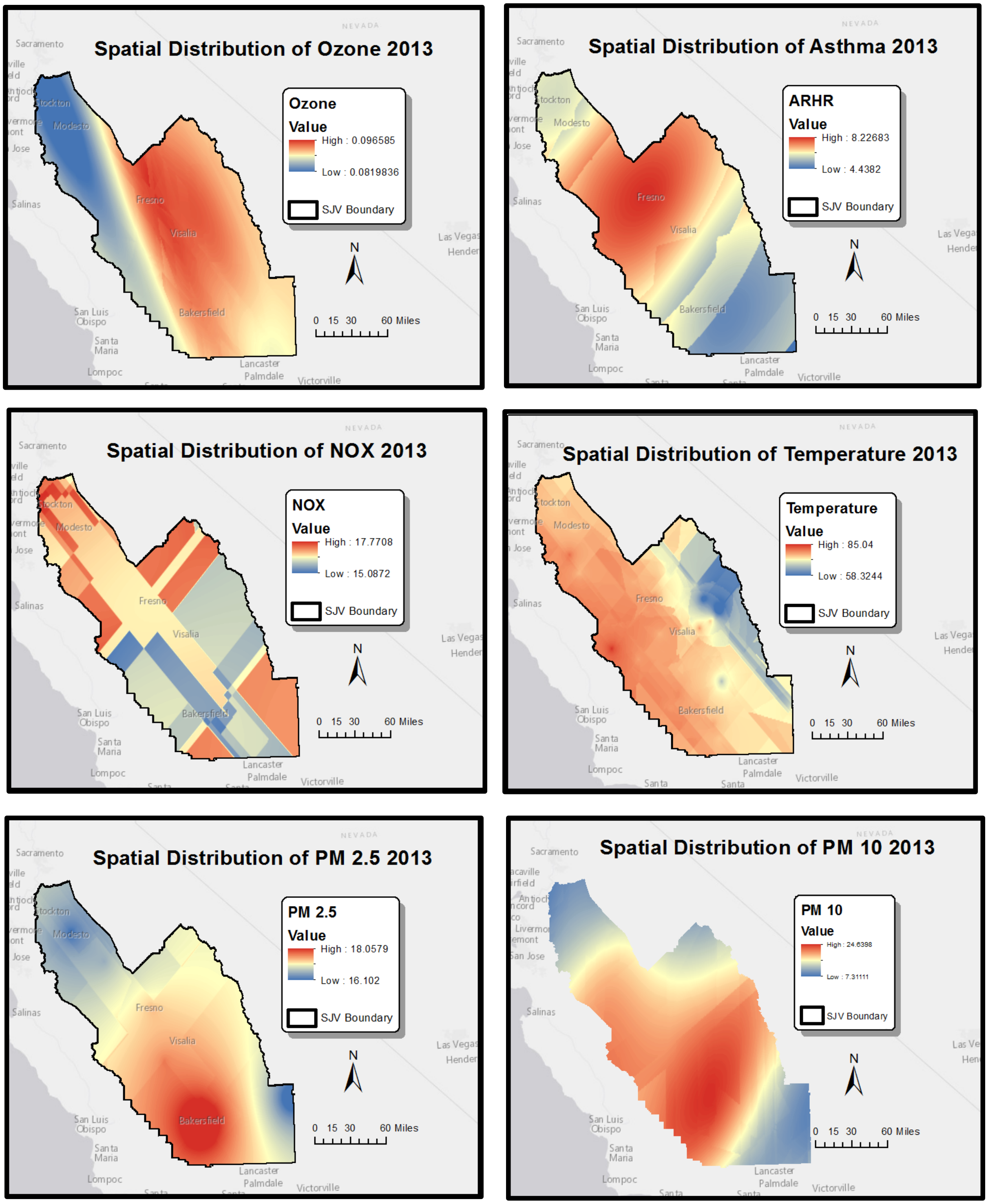



**Figure C2. Spatial Distribution Maps.** Showing average annual maximum ozone concentration (ppm), average annual maximum temperature, average annual $NO_{2}$, average annual PM2.5, average annual PM10 and average annual ARHR over SJV for the year 2013.

**Table C1. Data extracted for each study variable over the SJV area.** Data extracted from the spatial distribution maps for temperature, ozone, PM 2.5, PM 10 and ARHR used for the point regression analysis

| Temperature | | | Ozone (ppm) | | Nitrogen Oxides (ppb) | | | PM 10 (ug/cubic meters) | | | PM 2.5 (ug/cubic meters) | | | Asthma Hospitalization Rate | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Point # | 2011 | 2012 | 2013 | 2011 | 2012 | 2013 | 2011 | 2012 | 2013 | 2011 | 2012 | 2013 | 2011 | 2012 | 2013 | 2011 | 2012 | 2013 |
| | | | | | | | | | | | | | | | | | | |
| 1 | 70.569 | 71.138 | 70.000 | 0.0914 | 0.0879 | 0.0918 | 18.704 | 25.251 | 15.780 | 26.561 | 15.078 | 17.019 | 18.133 | 11.670 | 17.019 | 7.9400 | 7.0741 | 8.6286 |
| 2 | 66.712 | 65.995 | 67.428 | 0.0914 | 0.0899 | 0.0931 | 18.607 | 25.038 | 16.053 | 26.993 | 12.753 | 17.108 | 15.081 | 15.229 | 17.108 | 8.3938 | 6.9738 | 8.2750 |
| 3 | 77.777 | 76.876 | 78.678 | 0.0902 | 0.0950 | 0.0953 | 18.180 | 26.358 | 16.086 | 27.539 | 34.473 | 17.205 | 14.315 | 15.051 | 17.205 | 8.3333 | 7.6181 | 8.2750 |
| 4 | 78.056 | 78.405 | 77.707 | 0.0924 | 0.0941 | 0.0953 | 18.459 | 25.032 | 16.064 | 27.252 | 25.275 | 17.203 | 13.815 | 15.568 | 17.203 | 8.2625 | 7.2990 | 8.2750 |
| 5 | 78.975 | 78.547 | 79.403 | 0.0920 | 0.0948 | 0.0935 | 19.473 | 25.931 | 15.511 | 27.614 | 40.961 | 17.360 | 14.042 | 14.717 | 17.360 | 8.2214 | 7.3714 | 8.2750 |
| 6 | 72.527 | 71.472 | 73.583 | 0.0915 | 0.0885 | 0.0917 | 18.741 | 27.730 | 17.141 | 26.352 | 14.830 | 16.955 | 18.134 | 11.605 | 16.955 | 7.4800 | 6.5690 | 9.5167 |
| 7 | 77.678 | 77.400 | 77.956 | 0.0900 | 0.0927 | 0.0921 | 19.333 | 22.372 | 16.998 | 27.005 | 22.000 | 16.787 | 13.964 | 16.944 | 16.787 | 8.9812 | 7.6124 | 8.2750 |
| 8 | 77.472 | 77.387 | 77.556 | 0.0881 | 0.0966 | 0.0931 | 18.927 | 22.222 | 17.287 | 27.275 | 24.066 | 16.856 | 13.736 | 17.060 | 16.856 | 9.1000 | 7.7989 | 8.2750 |
| 9 | 78.604 | 78.136 | 79.072 | 0.0905 | 0.0912 | 0.0840 | 19.120 | 22.961 | 17.303 | 27.090 | 34.196 | 16.857 | 13.573 | 17.026 | 16.857 | 8.7729 | 7.6429 | 8.2750 |
| 10 | 79.099 | 78.762 | 79.436 | 0.0966 | 0.0925 | 0.0945 | 18.946 | 25.404 | 15.375 | 27.879 | 38.724 | 17.237 | 13.820 | 15.520 | 17.237 | 8.3333 | 7.8704 | 8.2750 |
| 11 | 78.636 | 77.264 | 80.008 | 0.0932 | 0.0902 | 0.0886 | 19.411 | 26.767 | 16.111 | 27.520 | 36.163 | 17.239 | 14.039 | 15.479 | 17.239 | 8.1765 | 7.6335 | 8.2750 |
| 12 | 77.775 | 77.315 | 78.235 | 0.0928 | 0.0929 | 0.0963 | 18.687 | 22.243 | 17.310 | 27.488 | 23.075 | 16.984 | 12.787 | 17.243 | 16.984 | 8.6040 | 8.1251 | 8.2750 |
| 13 | 76.391 | 75.893 | 76.889 | 0.0969 | 0.0930 | 0.0955 | 18.748 | 22.924 | 16.506 | 27.484 | 18.080 | 17.024 | 13.158 | 14.877 | 17.024 | 8.3436 | 8.1370 | 8.2750 |
| 14 | 73.220 | 73.319 | 73.121 | 0.0942 | 0.0900 | 0.0944 | 19.017 | 22.818 | 17.364 | 27.197 | 10.312 | 16.987 | 12.623 | 14.738 | 16.987 | 8.6933 | 7.9819 | 8.2750 |
| 15 | 77.212 | 76.521 | 77.903 | 0.0885 | 0.0935 | 0.0847 | 20.116 | 24.240 | 16.776 | 26.611 | 25.923 | 16.681 | 14.538 | 16.925 | 16.681 | 9.1184 | 7.0672 | 8.2750 |
| 16 | 77.416 | 76.501 | 78.331 | 0.0841 | 0.0905 | 0.0830 | 18.888 | 21.410 | 17.114 | 26.383 | 28.303 | 16.736 | 13.461 | 17.504 | 16.736 | 9.0941 | 7.1471 | 8.2750 |
| 17 | 78.488 | 78.969 | 78.007 | 0.0935 | 0.0974 | 0.0928 | 18.992 | 27.745 | 17.170 | 26.668 | 23.074 | 17.386 | 17.257 | 11.765 | 17.386 | 7.5385 | 6.4068 | 8.1800 |
| 18 | 78.983 | 78.960 | 79.006 | 0.0934 | 0.0958 | 0.0938 | 19.487 | 25.951 | 15.586 | 28.048 | 38.466 | 17.771 | 16.482 | 14.953 | 17.771 | 8.2214 | 6.9224 | 8.2750 |
| 19 | 75.729 | 76.162 | 75.295 | 0.0914 | 0.0882 | 0.0910 | 18.541 | 27.733 | 17.104 | 25.626 | 20.287 | 16.798 | 18.134 | 11.141 | 16.798 | 7.3308 | 6.7550 | 8.1800 |
| 20 | 77.863 | 77.825 | 77.902 | 0.0940 | 0.0905 | 0.0909 | 18.741 | 27.750 | 17.218 | 27.090 | 14.760 | 17.415 | 17.252 | 14.835 | 17.415 | 7.6947 | 6.5179 | 8.6286 |
| 21 | 78.563 | 79.433 | 77.694 | 0.0915 | 0.0930 | 0.0904 | 18.575 | 27.736 | 17.108 | 25.291 | 22.019 | 16.977 | 15.255 | 11.166 | 16.977 | 7.3308 | 6.6915 | 8.6286 |
| 22 | 79.031 | 79.258 | 78.804 | 0.0942 | 0.0964 | 0.0933 | 19.161 | 27.747 | 17.206 | 27.464 | 28.384 | 17.642 | 17.405 | 14.790 | 17.642 | 7.6333 | 6.8138 | 8.6286 |
| 23 | 77.667 | 77.616 | 77.718 | 0.0926 | 0.0947 | 0.0947 | 18.776 | 25.945 | 15.568 | 27.833 | 41.397 | 17.459 | 14.150 | 15.383 | 17.459 | 8.2471 | 6.6982 | 8.2750 |
| 24 | 75.951 | 76.669 | 75.233 | 0.0914 | 0.0859 | 0.0914 | 18.773 | 27.730 | 17.117 | 25.885 | 17.477 | 16.574 | 18.133 | 11.487 | 16.574 | 7.4311 | 6.6324 | 9.5167 |
| 25 | 79.831 | 78.958 | 80.705 | 0.0921 | 0.0879 | 0.0881 | 19.504 | 26.773 | 16.145 | 27.336 | 33.669 | 17.237 | 14.047 | 15.442 | 17.237 | 8.2375 | 7.4532 | 8.2750 |
| 26 | 75.038 | 73.898 | 76.178 | 0.0919 | 0.0918 | 0.0914 | 18.590 | 24.821 | 15.864 | 26.017 | 25.782 | 17.173 | 15.417 | 11.632 | 17.173 | 7.9097 | 6.3957 | 8.2750 |
| 27 | 79.745 | 78.846 | 80.644 | 0.0881 | 0.0888 | 0.0855 | 19.074 | 22.984 | 17.325 | 27.215 | 35.199 | 16.985 | 11.940 | 17.035 | 16.985 | 8.7733 | 7.9741 | 8.2750 |
| 28 | 75.141 | 75.109 | 75.174 | 0.0912 | 0.0942 | 0.0953 | 18.939 | 26.947 | 15.994 | 27.483 | 26.775 | 17.153 | 14.274 | 15.099 | 17.153 | 8.3333 | 7.8250 | 8.2750 |
| 29 | 82.525 | 82.478 | 82.571 | 0.0891 | 0.0846 | 0.0875 | 18.347 | 24.859 | 15.253 | 27.306 | 33.229 | 17.136 | 13.545 | 15.521 | 17.136 | 8.8375 | 7.9007 | 8.2750 |
| 30 | 79.519 | 78.684 | 80.353 | 0.0902 | 0.0878 | 0.0850 | 19.116 | 22.964 | 17.308 | 27.089 | 34.620 | 16.932 | 12.940 | 16.937 | 16.932 | 8.7635 | 7.7830 | 8.2750 |
| 31 | 68.097 | 66.606 | 69.587 | 0.0911 | 0.0845 | 0.0919 | 19.751 | 25.027 | 16.022 | 26.862 | 11.955 | 17.063 | 15.002 | 15.171 | 17.063 | 8.3562 | 7.0423 | 8.2750 |
| 32 | 71.435 | 71.463 | 71.406 | 0.0915 | 0.0807 | 0.0920 | 19.310 | 23.806 | 17.393 | 26.874 | 12.519 | 17.038 | 14.962 | 14.874 | 17.038 | 8.6460 | 7.5078 | 8.2750 |
| 33 | 76.600 | 76.949 | 76.25 | 0.0961 | 0.0947 | 0.0957 | 18.913 | 25.242 | 17.301 | 27.644 | 26.350 | 17.137 | 14.885 | 15.199 | 17.137 | 8.1500 | 8.1070 | 8.2750 |
| 34 | 67.044 | 67.837 | 66.251 | 0.0912 | 0.0834 | 0.0922 | 19.126 | 26.906 | 15.985 | 26.902 | 9.265 | 17.077 | 14.895 | 15.411 | 17.077 | 8.3562 | 7.3628 | 8.2750 |
| 35 | 76.443 | 76.472 | 76.414 | 0.0848 | 0.0905 | 0.0863 | 19.404 | 20.162 | 16.417 | 26.151 | 19.050 | 16.839 | 13.345 | 16.899 | 16.839 | 8.6176 | 7.0272 | 8.2750 |
| 36 | 76.879 | 76.383 | 77.376 | 0.0847 | 0.0877 | 0.0829 | 19.742 | 22.718 | 17.331 | 25.929 | 19.802 | 16.868 | 13.621 | 17.524 | 16.868 | 8.1025 | 7.0189 | 8.2750 |

## Appendix D: Tables of Regression Results 2011-2013

**Table D1. Results of the linear regression Analysis.** Showing adjusted $R^2$ values calculated using linear regression for each pollutant for the year 2011- 2013. The coefficient of determination ($R^2$ values) as a measure of fit for the regression models

| ASTHMA | TEMPERATURE | OZONE | NOX | PM 2.5 | PM 10 |
|---|---|---|---|---|---|
| **2011** | | | | | |
| **R-SQUARED** | -0.017850 | -0.024590 | 0.009034 | 0.334300 | 0.098110 |
| **P-VALUE** | 0.538500 | 0.691800 | 0.258800 | 0.000132 | 0.035280 |
| **2012** | | | | | |
| **R-SQUARED** | -0.028700 | -0.027090 | 0.608100 | 0.684700 | 0.764800 |
| **P-VALUE** | 0.886300 | 0.783300 | 0.000000 | 0.000000 | 0.000000 |
| **2013** | | | | | |
| **R-SQUARED** | 0.016630 | -0.017370 | 0.000374 | -0.006135 | -0.017370 |
| **P-VALUE** | 0.215600 | 0.530100 | 0.910900 | 0.381400 | 0.530100 |

**Table D2. Results of GWR.** Showing $R^2$ values calculated using GWR with P- Values for of each pollutant for the year 2011- 2013. The coefficient of determination ($R^2$ values) as a measure of fit for the regression models

| ASTHMA | TEMPERATURE | OZONE | NOX | PM 2.5 | PM 10 |
|---|---|---|---|---|---|
| **2011** | | | | | |
| **R-SQUARED** | 0.3621 | 0.8154 | 0.8594 | 0.8378 | 0.8547 |
| **P-VALUE** | 0.2275 | 0.4492 | 0.8152 | 0.0005 | 0.6854 |
| **2012** | | | | | |
| **R-SQUARED** | 0.1668 | -0.0179 | 0.7856 | 0.8188 | 0.8068 |
| **P-VALUE** | 0.0936 | 0.0106 | 0.8385 | 0.0001 | 0.0373 |
| **2013** | | | | | |
| **R-SQUARED** | 0.4792 | 0.1770 | 0.2674 | 0.1887 | 0.8591 |
| **P-VALUE** | 0.6248 | 0.9427 | 0.6851 | 0.8345 | 0.1888 |

**Table D3. Result of Regression Analysis**. Showing a matrix of correlation coefficients for each pollutant for the year 2011-2013. Used determine initial relationship strengths and directionality.

| | ASTHMA | NOX | OZONE | PM 2.5 | PM 10 | TEMPERATURE |
|---|---|---|---|---|---|---|
| **ASTHMA** | 1.00000 | | | | | |
| **NOX** | -0.78696 | 1.00000 | | | | |
| **OZONE** | -0.04748 | 0.05760 | 1.00000 | | | |
| **PM 2.5** | 0.83288 | -0.69333 | 0.05222 | 1.00000 | | |
| **PM 10** | 0.02470 | -0.00751 | 0.45975 | 0.16616 | 1.00000 | |
| **TEMPERATURE** | 0.18607 | 0.02695 | 0.44905 | 0.27934 | 0.70204 | 1.00000 |

| | ASTHMA | NOX | OZONE | PM 2.5 | PM 10 | TEMPERATURE |
|---|---|---|---|---|---|---|
| **ASTHMA** | 1.00000 | | | | | |
| **NOX** | 0.19326 | 1.00000 | | | | |
| **OZONE** | 0.10815 | -0.26452 | 1.00000 | | | |
| **PM 2.5** | 0.26452 | -0.45273 | 0.45370 | 1.00000 | | |
| **PM 10** | -0.15037 | -0.69333 | 0.22580 | 0.03802 | 1.00000 | |
| **TEMPERATURE** | 0.21148 | 0.03802 | 0.02744 | 0.17285 | 0.17286 | 1.00000 |

| | ASTHMA | NOX | OZONE | PM 2.5 | PM 10 | TEMPERATURE |
|---|---|---|---|---|---|---|
| **ASTHMA** | 1.00000 | | | | | |
| **NOX** | -0.19325 | 1.00000 | | | | |
| **OZONE** | 0.06841 | -0.22580 | 1.00000 | | | |
| **PM 2.5** | -0.35197 | 0.05584 | 0.46193 | 1.00000 | | |
| **PM 10** | 0.59444 | -0.16885 | 0.25337 | -0.36233 | 1.00000 | |
| **TEMPERATURE** | -0.10596 | -0.07616 | 0.01092 | 0.20153 | -0.20277 | 1.00000 |

# Appendix E: P-Values for Regression Analysis and Moran's I test on Residuals

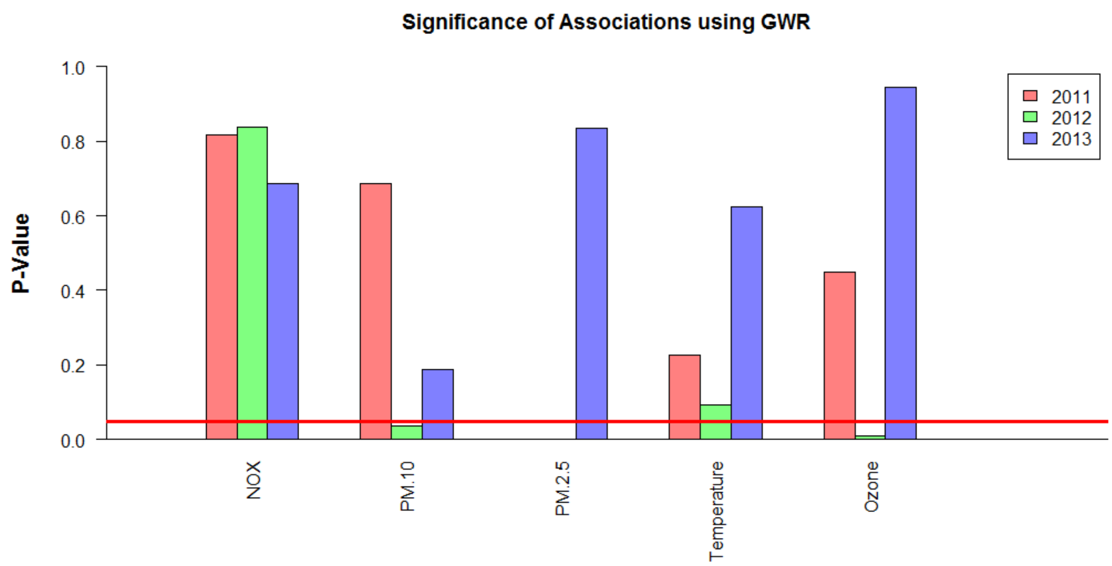



**Figure E1. Distribution of Parameter P-value used in GWR.** The bar plot shows the parameters P-Values used to assess significance of the global GWR model fit. Value below the 5% significance line are considered significant.

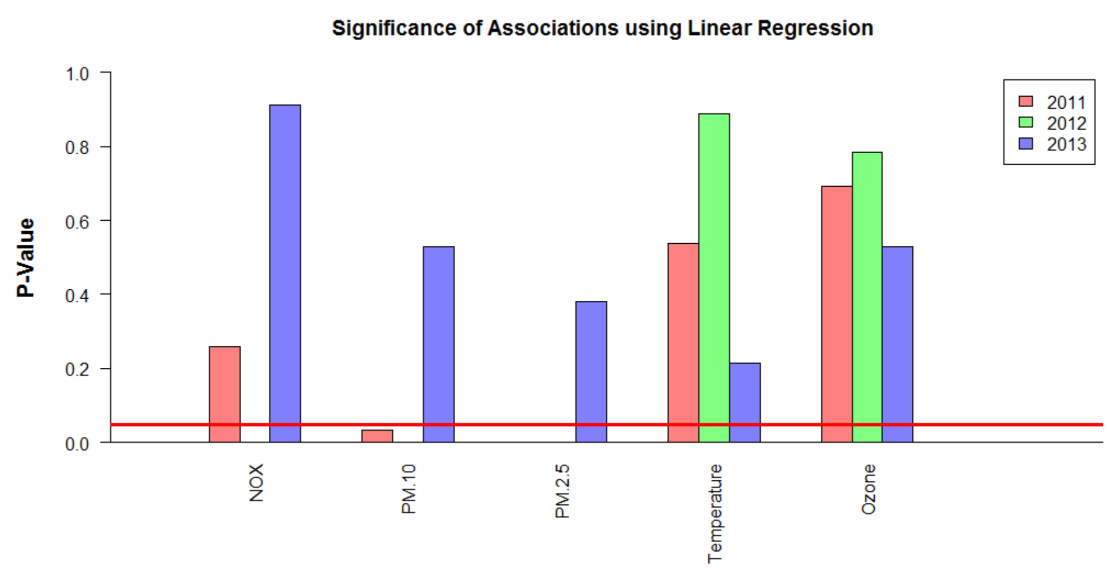



**Figure E2. Distribution of Parameter P-value used in linear regression.** The bar plot shows the parameters P-Values used to assess significance of the linear regression model fit. Value below the 5% significance line are considered significant.

**Table E3. Results of the test for spatial autocorrelation (Global Moran's I) on model residuals.** Showing the Moran's, I statistic size and significance of p-value. Clustering indicates a wrongly specified model and random distribution indicates an accurate model. No clustering is indicated in any of the significant model fits indicate a correctly specified model and reasonable error in residuals.

| GWR RESIDUALS | EXPECTED I | MORAN'S I | Z-SCORE | VARIANCE | P-VALUE | DISTRIBUTION |
|---|---|---|---|---|---|---|
| | | | | | | |
| **OZONE** | | | | | | |
| **2013** | -0.020408 | 0.296232 | 3.184637 | 0.009886 | 0.001449 | Clustered |
| **2012** | -0.034483 | 0.752071 | 7.587971 | 0.010364 | 0 | Clustered |
| **2011** | -0.020408 | 0.167341 | 1.866073 | 0.010123 | 0.062031 | Clustered |
| | | | | | | |
| **TEMPERATURE** | | | | | | |
| **2013** | -0.034483 | 0.160976 | 1.395175 | 0.019627 | 0.162963 | Clustered |
| **2012** | -0.020408 | 0.752071 | 7.587971 | 0.010364 | 0 | Clustered |
| **2011** | -0.034483 | 0.142391 | 1.165446 | 0.023033 | 0.243839 | Clustered |
| | | | | | | |
| **PM 2.5** | | | | | | |
| **2013** | -0.020408 | 0.088491 | 1.70341 | 0.009993 | 0.088491 | Clustered |
| **2012** | -0.020408 | 0.105532 | 1.269859 | 0.009836 | 0.204135 | Random |
| **2011** | -0.020408 | 0.128538 | 1.511089 | 0.009716 | 0.130766 | Random |
| | | | | | | |
| **PM 10** | | | | | | |
| **2013** | -0.021739 | 0.439777 | 4.579146 | 0.010158 | 0.000005 | Clustered |
| **2012** | -0.020408 | 0.307112 | 0.861681 | 0.009795 | 0.388863 | Random |
| **2011** | -0.020408 | 0.113048 | 1.338039 | 0.009948 | 0.180884 | Random |
| | | | | | | |
| **NOX** | | | | | | |
| **2013** | -0.019608 | 0.804183 | 10.533758 | 0.006116 | 0 | Clustered |
| **2012** | -0.020408 | 0.116908 | 1.374957 | 0.009974 | 0.169145 | Clustered |
| **2011** | 0.076795 | -0.020408 | 0.981619 | 0.009806 | 0.326288 | Clustered |

# Appendix F: Explanatory Regression Model for 2011 and 2013

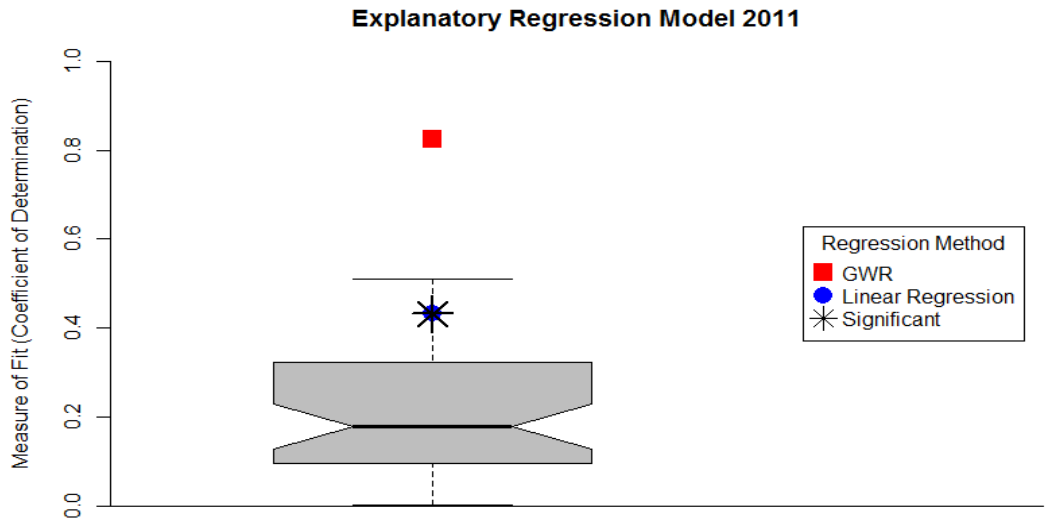



**Figure F1. Distribution of measure fit for Explanatory Regression Model 2011**. Local $R^2$ values are shown in the boxplot with the global GWR and linear regression result plotted for comparison. The adjusted $R^2$ value was used as the criteria for how well the model explained ARHR. PM 2.5 and PM 10 show a significant strong association for linear regression indicating an adequate model fit but was not significant for GWR.

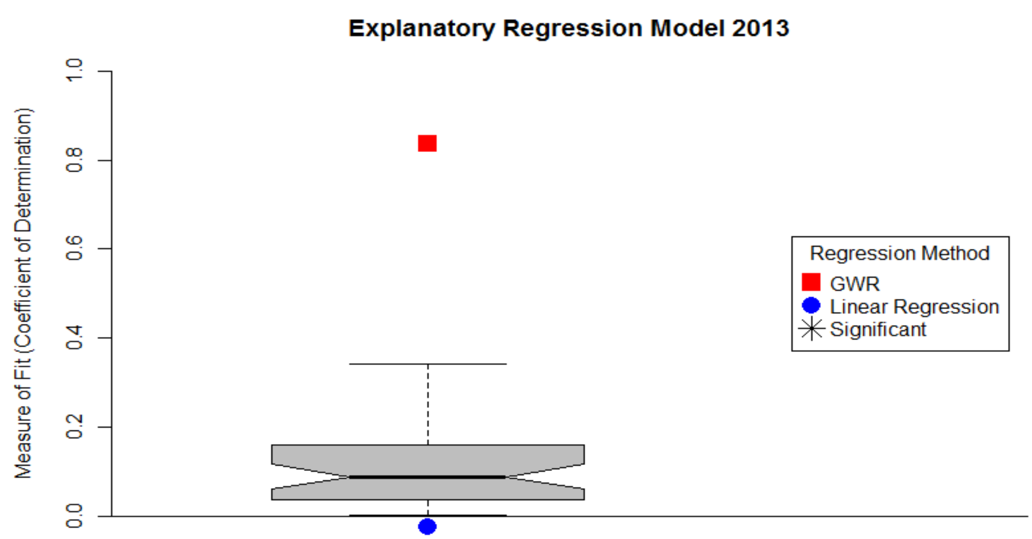



**Figure F2. Distribution of measure fit for Explanatory Regression Model 2013**. Local $R^2$ values are shown in the boxplot with the global GWR and linear regression result plotted for comparison. The adjusted $R^2$ value was used as the criteria for how well the model explained ARHR. PM 2.5 and PM 10 show no association for linear regression and GWR indicating a weak model fit for both global and local regression.