THE INFLUENCE OF METEOROLOGICAL PARAMETERS AND AIR POLLUTION ON EMERGENCY HOSPITALIZATION VISITS OF CARDIOVASCULAR AND RESPIRATORY DISEASES IN COASTAL BEND, TEXAS

A Thesis

by

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This thesis meets the standard for the scope and quality of
Texas A&M University-Corpus Christi and is hereby approved.

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August 2019

ABSTRACT

Cardiovascular diseases and Respiratory diseases are the leading causes of death globally. The objective of this thesis is to investigate the associations between meteorological parameters, air pollution, and emergency department (ED) visits for Cardiovascular and Respiratory diseases, respectively in Coastal Bend, Texas.

A complete ED Hospitalization visits data were obtained from the local hospital systems through 1 October 2010 to 31 August 2012. There were 58,665 visits diagnosed as Respiratory diseases and 18,252 visits diagnosed as Cardiovascular diseases. Air pollution data were obtained from the Environmental Protection Agency (EPA) and meteorological parameter data were downloaded from Weather Underground website. Generalized additive models (GAM) were applied to Respiratory diseases, while generalized linear models (GLM) were applied to Cardiovascular diseases. These models with the controlling for different time trends aimed to explore the associations of meteorological parameters and air pollution with daily counts of ED visits. The impact of the warm as well as the cold seasons and spatial differences were also examined. Distributed lag nonlinear models (DLNM) were applied to explore the effects of the air pollutants and meteorological parameters on the current day (lag 0) morbidity to the first seven days (lag 7). The study area is divided into three sub areas and their spatial variances on the influence of meteorological parameters on Cardiovascular and Respiratory diseases were also explored.

Our main findings on Cardiovascular diseases are air pollutants like $PM_{2.5}$, PM_{10} and meteorological parameters like Temperature, Relative Humidity, and Precipitation have significant associations with ED visits of Cardiovascular. The influence of PM_{10} and SO_2 both decreases during the cold season, but it increases during warm season. Precipitation presents

different influence patterns on Cardiovascular diseases spatially with significant association exists in one area, whereas no association presents in other areas. As for Respiratory diseases, considerable influence is observed from air pollution variables (SO_2, Ozone, $PM_{2.5}$, PM_{10}) and meteorological parameters (Temperature, Relative Humidity, Precipitation). Ozone has a significantly positive influence on Respiratory diseases during the cold season while no significant association exists during the warm season. The same pattern is observed on the influence of Precipitation on Cardiovascular diseases.

In conclusion, both meteorological parameters and air pollution have significant effects on ED visits for both Cardiovascular and Respiratory diseases in Coastal Bend, Texas. These findings may have implications for local hospitalization prevention policies.

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CHAPTER I: INTRODUCTION

1.1 BACKGROUND

Cardiovascular diseases are a group of disorders of the heart and blood vessels that can refer to several conditions: heart disease, heart attack, stroke, heart failure, arrhythmia, and heart valve problems (AHA, 2017). According to the 2018 annual report from American Heart Association, Cardiovascular diseases, as the leading cause of death in the United States, is responsible for 840,768 deaths (almost 30.6% of all deaths). About 92.1 million adults are having some type of Cardiovascular disease or sequela caused by stroke. Among all types of Cardiovascular diseases, Coronary Heart Disease makes the leading cause (43.8%) of deaths, followed by Stroke (16.8%), and other Cardiovascular diseases (17.9%). The direct and indirect costs made by Cardiovascular diseases that includes health expenditures as well as lost productivity comes up to $329.7 billion per year (AHA, 2018).

Respiratory diseases are chronic diseases of the airways and other structures of the lung that can refer to asthma, chronic obstructive pulmonary disease (COPD), occupational lung diseases and pulmonary hypertension. Respiratory diseases are a group of important diseases which rank number four in the 10-leading causes of death in the United States, causing 154,596 deaths (around 5.6% of all deaths) in the year of 2016 (CDC, 2017). As reported by Office of Disease Prevention and Health Promotion, there are more than 25 million people suffer asthma in the United States, approximately 14.8 million adults have been diagnosed with COPD, while approximately 12 million people have not yet been diagnosed (ODPHP, 2019). The direct medical costs due to Respiratory disease projected to increase to an estimated 49 billion dollars annually by 2020 (CHEST, 2014).

The effects of these diseases are not limited to only the patients. There are many stakeholders involved in the diseases. For example, families, schools, workplaces, neighborhoods, cities, and states have huge burdens due to Cardiovascular and Respiratory diseases. Cardiovascular and Respiratory diseases care can be financed through health insurance. Since Medicare or Medicaid insurance are enrolled in individuals suffering from these diseases, the burden then falls on society at a price of tax dollars, higher health insurance rates, and lost productivity (Cardiovascular Disease in the United States, 2013; ODPHP, 2019).

Meanwhile, Cardiovascular and Respiratory diseases are the leading causes of death in Texas (Texas Department of State Health Services, 2017). It is reported that, about 113 hospitalizations due to heart disease occurred, and about 28 hospitalizations due to stroke occurred every year for every 10,000 adults in Texas. In 2014, an estimated 1.78 million Texas adults reported currently having asthma, and an estimated 1.1 million Texans have COPD. The cost of treatment of Cardiovascular and Respiratory diseases is extremely high. According to Texas Department of State Health Services, a total expenditure of 559 million dollars have been spent on Cardiovascular diseases in the fiscal year 2015 in Texas. In the fiscal year 2014, a total of 118.5 million dollars expenditures for child and adult asthma acute care was claimed, and a total of 78.9 million dollars expenditures for all acute care COPD was claimed (Texas Department of State Health Services, 2017). It is necessary to address the prevention and avoid the exacerbation of Cardiovascular and Respiratory diseases. Even a small percentage of ED visits decrease can lead to a significant reduction in annual cost.

Many studies have found associations between ambient air pollution, meteorological factors and acute exacerbations of Cardiovascular diseases and Respiratory diseases (Lee, Jang H., et al. 2011; Winquist, A., et al. 2012; Vanos, J. K., et al. 2014; Jhun, I., et al. 2015; Phosri, A., et al. 2019). Studies also found complex relationships between ambient air pollution and meteorological factors, the covariance of ambient air pollution and meteorological factors can result in a high likelihood that the effect of one variable could modify the effect of the other (Jennifer et al., 2014). Moreover, many researches have demonstrated that, "given advanced warning of increased risk of Cardiovascular and Respiratory diseases, patients are better able to control their symptoms by a combination of medication, environmental, and behavior modifications" (Hansel, N., et al. 2016; Enard, K. R., & Ganelin, D. M. 2013; Thompson, P., et al, 2003).

Texas Coastal Bend area is the coastal area along the Gulf of Mexico with its ecosystems very sensitive to changes in the environment and natural phenomenon, including hurricanes and El Niño (The Environmental Literacy Council, 2015). Meteorological parameters in this study area can change suddenly and significantly, especially during hurricane seasons. At the same time, the five refineries within this study area are always considered as potential factors that can affect local air pollutions to some degrees.

1.2 STUDY AREA

The Texas Coastal Bend is an area along the coast of the Gulf of Mexico (Figure 3.1) with a total population of approximately 634,255 in 2010. It radiates out from Corpus Christi and includes 15 counties, Aransas, Bee, Brooks, Duval, Goliad, Jim Hogg, Jim Wells, Karnes, Kenedy, Kleberg, Live Oak, McMullen, Nueces, Refugio, and San Patricio.

The Coastal Bend area has always been posed to the threaten of hurricanes which responsible for a significant amount of damage to coastal ecosystems. Hurricanes can deplete food supplies, displace marine, and other wildlife and disrupt the ecosystem's balance (The Environmental Literacy Council, 2015). In August 25th, 2017, hurricane Harvey made landfall in Coastal Bend area, caused nearly $125 billion in damage and led to an estimated of 94 the deaths (The Texas Tribune, 2018). In addition to the social and economic impacts, Harvey raised environmental and public health concerns due to after-effects of flood events. (HARC, 2019).

The air pollution level in this area is unpredictable due to the emissions from industrial (The Environmental Literacy Council, 2015). As reported by The Environmental Literacy Council, the emissions runoff from industrial within this area is likely to result in higher nutrient or pollutant levels in coastal waters, fueling algae blooms which can be dangerous to both humans and marine life. There are five oil refineries within Coastal Bend Area: Three Rivers Refinery (Valero), Corpus Christi Complex (Flint Hills Resources), Corpus Christi Refinery (Citgo), Corpus Christi West Refinery (Valero), Corpus Christi East Refinery (Valero). Four of the refineries are located within Corpus Christi, the city with the largest population (approximately 309,3384) in the Coastal Bend area. It is undeniable that these refinery industries have boosted the local economy, but the toxic chemical and air pollution released by these refineries might affect the local inhabitants. The heavy industry that pumps out greenhouse gases warming the climate, increasing the risks of powerful storms that, in turn, endanger those same facilities and everything around them (The Texas Tribune, 2018). The Federal Agency for Toxic Substances and Disease Registry said in 2016, that inhaling the mixture of chemicals discharged in the area known as Refinery Row over the long term increases the risk of cancer. The agency also said that hydrogen sulfide, a gas with a rotten-egg stench that's deadly at high levels, regularly wafts over the area at concentrations that can cause headaches and difficulty breathing (ATSDR, 2016).

1.3 PURPOSE AND HYPOTHESIS

The main purpose of this study is to evaluate the short-term effect of meteorological parameters and air pollutions on human health by analyzing the Emergency Department (ED) visits of Cardiovascular and Respiratory diseases in Coastal Bend areas. In addition, the study explores the spatial variances of these influence factors on morbidity. We studied both Cardiovascular and Respiratory diseases because there are lots of similarities in the triggers of these diseases.

The objectives for the investigation of Cardiovascular diseases are listed below:

1. To explore the temporal influence of meteorological parameters and air pollutions on ED visits of Cardiovascular diseases.
2. To investigate the impact of meteorological parameters on ED visits of Cardiovascular diseases spatially within the Coastal Bend area.

The hypotheses of Cardiovascular diseases research are:

1. Higher concentrations of air pollutants and dramatic change in Temperature would be positively related to an increasing number of Cardiovascular ED visits.
2. The effect of meteorological parameters on ED visits of Cardiovascular might spatially exist within the study area.

The objectives for the investigation of Respiratory diseases are listed below:

1. To explore the temporal influence of meteorological parameters and air pollutions on ED visits of Respiratory diseases.

2. To investigate the impact of meteorological parameters on ED visits of Respiratory diseases spatially within the Coastal Bend area.

The hypotheses of Respiratory diseases research are:

1. Higher concentrations of air pollutants and dramatic change in Temperature would be positively related to an increasing number of Respiratory ED visits.
2. The effect of meteorological parameters on ED visits of Respiratory might spatially exist within the study area.

CHAPTER II: LITERATURE REVIEW

2.1 AIR POLLUTION

Review of numerous epidemiological time-series studies, a common conclusion has been found that increasing exposure to ambient air pollutants have a considerable determinant of the morbidity and mortality of Cardiovascular and Respiratory diseases (Jennifer et al., 2014; Hansel, N. N., et al. 2016; Nhung, Nguyen T. T., et al., 2018; Phosri, A., 2019). Sulfur Dioxide (SO_2), Ozone, Particulate matter with diameter smaller than 2.5 ($PM_{2.5}$), and Particulate matter with diameter smaller than 10 (PM_{10}) are the common variables that have been found causing influence on human health. SO_2 is a gas formed when fuel containing sulfur which can cause breathing difficulty for asthmatic patients. Exposure to high levels of SO_2 gas and particles for a long term may result in breathing difficulty for asthmatic patients, thereby causing or aggravating Respiratory disorders and Cardiovascular diseases (Poursafa P et al., 2011). Ozone, well-known as the greenhouse gas, is a gas composed of three oxygen atoms. It increases the lung permeability which affects cardiac function in turn. $PM_{2.5}$ and PM_{10} links Cardiovascular and Respiratory diseases because it can be inhaled and get deep into lungs and some may even into bloodstream (EPA, 2009)

The air pollution-related health impacts do not always present the same trend. It presents geographical differences and depends on the number of pollutants emitted, the meteorological conditions that influence the amount of air pollutions and the cumulative days (USGCRP, 2019). For example, studies in Hefei, China and Tianjin, China reported that with every increase of 10 $\mu g/m^3$ in PM_{10} levels, Cardiovascular mortality increased by 0.68% (95%CI: 0.33%–1.04%) and 0.19% (95% CI: 0.08%–0.31%) respectively, while a study in Wuhan, China found no statistically significant association between PM_{10} level and Cardiovascular mortality (Zhang C et al., 2017; Tong, L et al., 2014; Liu Y et al., 2015). A study in Ahvaz, Iran observed that ambient O_3, NO, NO_2 CO and SO_2 can increase admission for Respiratory diseases on the same day and at short lags (Dastoorpoor, M et al., 2019). At the same time, the study in Hefei, China revealed SO_2, NO_2, and PM_{10} are associated with an increase in Respiratory diseases mortality (Zhu, F et al., 2019).

2.2 METEOROLOGICAL PARAMETERS

Exposure to weather elements is also determinant of daily mortality and morbidity on Cardiovascular and Respiratory diseases. The influence of weather factors is more complicated because it can vary and co-vary with exposure to air pollution, thus modify estimates of ED visits (U.S. Global Change Research Program, 2019). As explained in the study conducted by Radaideh, with an increase in Relative Humidity, the concentration of CO increases by 15.2%, SO_2 by 21.6% and Ozone by 16% (Radaideh JA, 2017).

Relative Humidity, Wind Speed, Temperature and Precipitation are the common meteorological factors that would be involved in research related to Cardiovascular and Respiratory diseases (Jie, Y et al., 2014; Mittleman et al., 2011; Lam, HCY, et al., 2016).

2.3 METHODS

2.3.1 Pearson's Correlation

Pearson's correlation can evaluate the strength of statistical relationship between two continuous variables. Correlation coefficients range from -1 through 0 to +1. In general, values closer to -1 or +1 indicate more significant negative or positive correlation existed between measured variables. Values between + 0.5 and +1 or between – 0.5 and -1 means a strong correlation. A correlation coefficient of 0 would indicate no relationship exists between the two variables (Sedgwick, Philip., 2014).

2.3.2 Generalized Linear Model

The generalized linear model (GLM) can measure and analyze simultaneous effects of multiple explanatory variables on a dependent variable during temporal change. The result can then be used to explain whether an explanatory variable is related to the dependent variable and the strength association between this variable and the dependent variable. This model does not have strict requirements on data distribution. The dependent variable can be continuous or discrete, and the explanatory variables can be either quantitative or categorical. In addition, not only normal distributed variable is allowed, error distribution of response variable also applies to this model (Calcagno, V., & Mazancourt, C. d. 2010). GLM related explanatory variables with dependent variable mean in terms of a chosen link which can arrange the explanatory variables in a transformed order. After that, GLM analyzes the inter-relationship by assuming linear relationship between the dependent variable and the transformed data (Çapraz, et al., 2016).

2.3.3 Generalized Additive Model

Generalized Additive Model (GAM) is the combination of GLM and Addictive model. Addictive models represent multiple regressions to predict the relationship between response and predict variables. Therefore, in addition to make a single linear regression, GAM established multiple linear regression to predict the relationship between explanatory variables with dependent variable. This allows the transformed explanatory variables to be related to the predictor variables not just through coefficients, but through whole partial response functions. The advantage of using GAM is the ability to achieve the best prediction between predictor and response variables that even have highly non-linear and non-monotonic relationships (Guisan, A. et al., 2002).

2.3.4 Relative Risk

Relative Risk (RR) is an exponentiated coefficient that refers the probability of an event occurring in one group compared to the likelihood of an event occurring in the other group. It calculates the exponentiated coefficients between dependent variable and explanatory variables in GLM and GAM. A relative risk more than 1 suggests that a significant impact of explanatory variables on dependent variable is likely to occur.

2.3.5 Distributed Lag Model

Distributed lag model (DLNM) predicts dependent variable value on the current day based on the response variables values on the current lag and lagged days. It uses the distributed lag function, which estimates the RR change of an explanatory variable in continues day with a given data increase range, to evaluate the delay effect of explanatory factors on dependent variable (Çapraz, et al., 2016). This methodology allows the effect of a single exposure event to be distributed over a specific period, using several parameters to explain the contributions at different lags, thus providing a comprehensive picture of the time-course of the exposure-response relationship (Gasparrini, A. 2011). Distributed lag model can be applied to both GLM and GAM.

2.3.6 Global Moran's I

Global Moran's I measures spatial autocorrelation based on feature locations and feature values simultaneously. It measures the spatial pattern of geographical data by computing and comparing the given feature attribute data. This tool first computes the mean and variance of given data, then subtracts the mean and create a deviation from the mean, after that generates a cross-product with the multiple neighboring deviation values. The tool also compares the neighboring deviation values to determine if any pattern exists (ArcGIS Desktop, 2019). The pattern can be clustered, dispersed, or random.

The result is also normailized by a scale ranging from -1 through 0 to +1. The negative Index value indicates a dispersed pattern whereas high values repel other high values and tend to be near low values. The positive Index value indicates a cluster pattern whereas the values for neighboring features are either both larger than the mean or both smaller than the mean. The Index value of 0 means positive cross-product values balance negative cross-product values which can refer to the random pattern (ArcGIS Desktop, 2019).

2.3.7 Getis-Ord Gi*

Getis-Ord Gi* calculates the statistic for each feature in a dataset. This tool works by looking at each feature within the context of neighboring features. A feature with a high value and be surrounded by other features with high values as well would be considered as a statistically significant hot spot. And a feature with a low value and be surrounded by other features with low values as well would be considered as a statistically significant cold spot. This method also generates a 90%, 95% and 99% confidence interval of both hot spot and cold spot (ArcGIS Desktop, 2019).

CHAPTER III: METHODOLOGY

3.1. DATA AND DATA SOURCE

3.1.1 Hospitalization Data and Selection of Diseases

The hospitalized patients' information was obtained from all local hospital systems (Christus Spohn Hospital Corpus Christi, Corpus Christi Medical Center, Driscoll Children's Hospital) in Coastal Bend area from 1 October 2010 to 31 August 2012. The data contains several attributes, such as discharge date, home zip code, patient's age, patient's gender, diagnose code, etc. The data was aggregated by Zip Code Tabulation Areas (ZCTAs). Only data with valid zip code within the study area were kept for this study.

The Cardiovascular and Respiratory Diseases patient data were selected according to the diagnose code in the International Classification of Diseases tenth revision (ICD-10). In this code, all diseases have been classified and categorized into ICD: A00 – R99, Cardiovascular diseases are code from ICD: I00 – I99, Respiratory Diseases are code from (ICD: J00 – J99). However, the diagnose code in our data adopted the ninth version which is not as specific as the tenth version. Since most of the studies related to Cardiovascular and Respiratory diseases provided the ICD-10 code, this study used ICD-10 code. A conversion list of ICD-9 code to ICD-10 code for Cardiovascular and Respiratory diseases was made. This list was made by finding corresponded ICD-9 code of specific ICD-10 code through the website (https://www.icd10data.com/Convert). One ICD-10 code can correspond to multiple ICD-9 codes while one ICD-9 code can also correspond with several ICD-10 codes. For Cardiovascular diseases, the 628 tenth codes from ICD-10: I00 – I99 have 297 corresponded ninth code ranging from ICD-9: 390.00 to ICD-9: 997.71. And for Respiratory diseases, the 277 tenth codes from

ICD-10: J00 – J99 have 200 corresponded ninth code ranging from ICD-9: 460.00 to ICD-9: 997.32. After that, the ED visits data of Cardiovascular diseases was extracted by selecting data have the same diagnose code with the converted new ICD-9 code of Cardiovascular diseases. Meanwhile, the same method was applied to the ED visits data of Respiratory diseases.

3.1.2 Boundary data

Geographic boundary data were obtained from the United States Census Bureau TIGER/Line Geodatabase (https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-geodatabase-file.html). It was the 2010 5-digit zip code tabulation area data of whole Texas area. The boundary of these 15 counties within the Coastal Bend area was drawn. Baes on that, the zip code tabulation area of Coastal Bend, with a total of 94 zip codes was extracted.

3.1.3 Meteorological data

Daily Meteorological data such as average Temperature, Relative Humidity, Wind Speed, and Precipitation from 1 October 2010 to 31 August 2012 were downloaded from the Weather Underground website (https://www.wunderground.com/about/data). This website provides daily historical weather data of local airport station. There were 17 stations within or nearby Coastal Bend areas that provide the daily meteorological data. They are KRKP, KHBV, KALI, KNQI, KBKS, KRBO, KNOG, KTFP, KBEA, KCOT, KPEZ, KVCT, KRAS, KCRP, KNGP, KHRL, KPKV.

3.1.4 Air Pollution data

Air Pollution data were obtained from the US Environmental Protection Agency (EPA)'s Air Quality System (https://www.epa.gov/outdoor-air-quality-data). This data included max 1-hour sulfur dioxide (SO_2) in parts per billion (ppb), max 8-hour Ozone in parts per million (ppm), mean particular matter with diameters less than 2.5 micrometers ($PM_{2.5}$) and 10 micrometers (PM_{10}) in micrograms per cubic meters (ug/m3). PM_{10} data was only provided by one station, ozone data was provided by two stations while SO_2 and $PM_{2.5}$ data were available from three stations in the Coastal Bend area (Figure 3.1). Their average values were used. The missing data were filled by taking the mean value of the neighboring days.

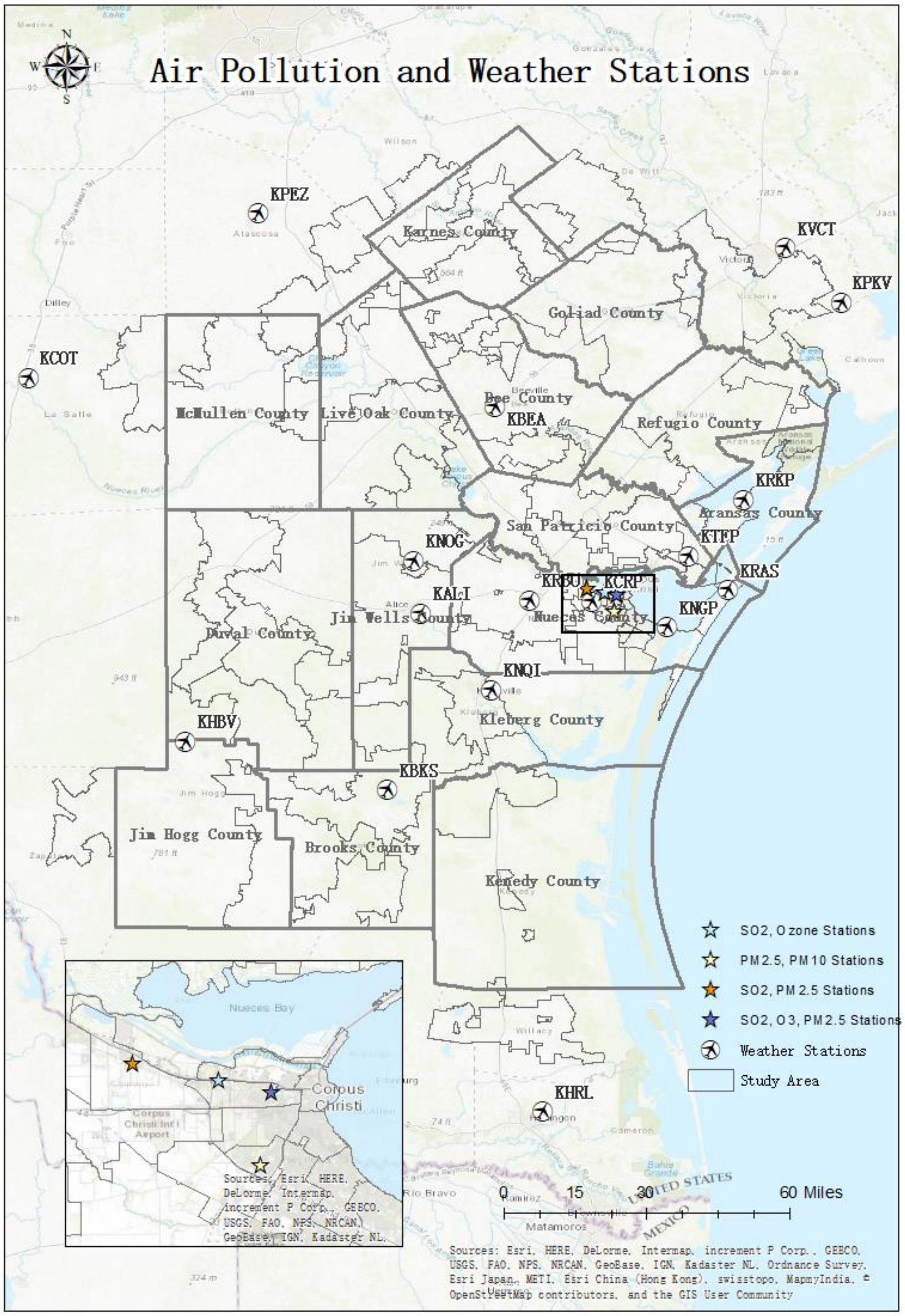


Figure 3.1 Air pollution and Weather Stations

3.2. STATISTICAL ANALYSIS

3.2.1 Correlation between air pollutants and weather conditions

Pearson's correlation coefficient was calculated to evaluate the inter-relation between air pollutants and meteorological parameters. A table that only contains daily air pollutants and meteorological parameters data during the study period was first generated. Then the data was inputted into the correlation function which can produce correlations in R. The method "pearson" was chosen among the three methods "person", "Kendall" and "spearman" while "complete.obs" was used to avoid errors that could be caused by missing data.

3.2.2 Relationship between meteorological parameters, air pollutions, and ED visits of Cardiovascular diseases.

The Poisson GLM was used to analyze the influence of air pollutants and meteorological parameters on Cardiovascular ED Visits. There were three steps in this process. The first step was to build the best basic model, which only includes air pollutions and meteorological variables for ED visits data. In this step, a smooth curve was fit to the time-series data by using a natural spline to control long-term trends for the day of study. This was because we have a small number of daily patient data (Cakmak et al., 2006). Specifically, 4 – 7 degree of freedom (df) were used for time trend to get the best model. The optimal model was then selected based on the time interval that minimized the Akaike's Information Criteria (AIC), a measure of model prediction. The residuals of the model with minimum AIC was tested by partial autocorrelation function (PACF) to determine if there was an autocorrelation between the model residuals thereby verifying the selection of model parameters. The basic model was regarded as adequate if the absolute magnitude of the PACF plot was less than 0.1 for the first two lag days.

In the second step, all variables were added to the basic model. Day of the week (DOW) was included as dummy variables to adjust the temporal trend. Meanwhile, air pollutants (SO_2, Ozone, $PM_{2.5}$, and PM_{10}) and meteorological parameters (Temperature, Relative Humidity, Wind Speed and Precipitation) were added to the established basic model. In this study, we built a total of 31 models in the investigation of Cardiovascular diseases by means of adding only single variables and the combination of variables to observe whether the impact differs after adding other influence variables. 15 models only include air pollutants variables and 15 models only contains meteorological parameters and the other one involved all the air pollutants and meteorological factors. After that, ANOVA chi-square test was performed to the fitted models to assure the significance.

Finally, to facilitate comparisons across all explanatory variables, the RR and the RR with 95% Confidence Intervals (CI) for one interquartile range (IQR) increment in the level of the respective explanatory variables of RR was generated.

The final model is as below:

$$\log[E(Yt)] = \alpha + ns(time, df) + DOW + \beta Zt$$

Where t refers to the day of the observation; E(Yt) is the number of ED visits to be estimated on observation day t; α is the intercept; ns (time, df) denote a regression spline function for the time of study that has been divided by a specific degree of freedom; DOW is the day of the week on day t; βZt represent the log-relative rate of ED visits associated with a percentage increases of Z variable on concentration on day t (ZHANG Y, et al,. 2015).

The R code is listed below:

Estimated Cardiovascular ED visits <- glm(Cardiovascular ED visits recored~ ns(study time, df = 6) + DOW + SO2 + Ozone + PM2.5 + PM10 + Temperature + Relative Humidity + Wind Speed + Precipitation, data = data, family = poisson())

Additionally, season-specific analyses for air pollutants variables between warm (May to October) and cold (November to April) seasons were conducted. A binary variable was created for the season in data, with 0 denotes as the warm season and 1 denotes as the cold season. Adjusted GLM model with passion regression including all the time trends and air pollutants variables and choosing the degree of freedom that better fits the data was conducted for warm and cold season respectively. The relative risk was reported separately so as to make a comparison. All statistical analyses were conducted in R using the “mgcv” and “spline” packages.

3.2.3 Relationship between meteorological parameters, air pollutions, and ED visits of Respiratory Diseases.

The Poisson GLM was also applied to Respiratory Diseases. However, autocorrelation existed among the model residuals. In this case, the Poisson GAM was adopted. In addition, auto-regression (AR) term was introduced to improve the model. GAMs have the same process as GLMs in model establishing, except the correlation function was added into the GAM core model. After adjusting the GAM model with Poisson regression including all the time trends and correlation, explanatory variables were added into the fitted model. The number of models in the investigation of Respiratory diseases stays the same with Cardiovascular diseases. There were 15 models in total to explore the influence of single or the combination of several explanatory variables on ED visits of Respiratory diseases. After that, the relative risk with 95% CI of each variable in all models was reported. In addition, season-specific analyses for air pollutants variables between warm (May to October) and cold (November to April) seasons were conducted using the same method as mentioned in Cardiovascular diseases. All statistical analyses were performed in R using the “mgcv” and “spline” packages.

The R codes is listed below:

Estimated Respiratory ED visits <- gamm(Respiratory ED visits recored ~ s(study time, k=70) + DOW + SO2 + Ozone + PM2.5 + PM10 + Temperature + Relative Humidity + Wind Speed + Precipitation, correlation=corAR1(), family = poisson())

3.2.4 Lag day effects

The DLNM have been applied here to examine delayed effects with the single and overall cumulative lag days (from L0 to L7) for both air pollutions and meteorological parameters. First of all, each explanatory factor has been put into crossbasis () function which generates the basis matrices for the two dimensions of predictor and lags, given the functions selected to model the relationship in each space. Then the single pollutant model was built including the basised factors as an explanatory variable. After that, the basised factor and the associated model were added into the crosspred () function that generates specific effects for each combination of values and lags, plus overall and cumulative effects. Finally, the estimated effects and 95% confidence interval (CI) of the percentage of the increases of each explanatory variables on lag days from the current day (lag0) to lag 7 days were expressed through plot () function. In this study, 10-unit increase in SO_2, PM_{10}, $PM_{2.5,}$ Temperature, Relative Humidity, Wind Speed and 0.1-unit increases in Ozone and Precipitation over 7 days of lag were observed. Due to the low Ozone level and the small Precipitation amount in the Coastal Bend area. Therefore, only 0.1 unit increase of these two variables would be better fitted in the comparison of delayed effects.

3.3. SPATIAL ANALYSIS

3.3.1 Spatial Patterns

Spatial Autocorrelation (Global Moran's I) was employed to assess the overall pattern and trend of ED visits ratio data. Getis-Ord Gi* (Hot Spot Analysis) was applied to identify the pattern of ED visits data within the zip code of neighboring zip code and compared the local situation to the global situation. This analysis were performed in ArcGIS. In this process, the ED visits data have been normalized by the population data within that zipcode to generate the ED visits ratio data.

3.3.2 Spatial Variation

The method we used in exploring the relationship between meteorological parameters, air pollutions and ED visits were applied to detect the spatial variation. Only meteorological parameters were used as explanatory variables because air pollution data provided in this study do not have spatial attributes, all air pollution stations are concentrated at Corpus Christi. The study area was divided into three sub-areas based on the county’s spatial extent and the distirbution of weather stations (Figure 3.2). Sub-area 1 consists of the six counties in the east of the study area near the coastal. These are Kenedy, Kleberg, Nueces, San Patricio, Refugio, and Aransas counties. Sub-area 2 located in the north part including 5 counties: McMullen, Live Oak, Bee, Goliad, and Karnes. The rest four counties, including Brooks, Duval, Jim Hogg, Jim Wells locate in the southwest and they belong to sub-area 3.

Since the study area was separated into three parts, the ED visits data and meteorological data were also rearranged into three components corresponding to the sub-areas. The Temperature, Relative Humidity, Wind Speed and Precipitation data within each sub-area were calculated by averaging those station data belongs to this area. GLM for Cardiovascular diseases and GAM for Respiratory diseases were conducted three times for each of the sub-areas respectively. After that, the relative risk of meteorological parameters were reported and analyzed to identify the spatial variance of the influence of meteorological parameters on Cardiovascular diseases and Respiratory Diseases.

Figure 3.2 Sub-areas of Coastal Bend area.

CHAPTER IV: RESULTS

4.1. DESCRIPTIVE ANALYSIS

In this study period, a total of 480,324 ED visits was identified for the study. Among the ED visits, 122,386 are child under 18 years old, 292,960 are adults from 18 to 65 years old and 64,978 are senior visits above age 65. In addition, 58,665 patients are diagnosed as Respiratory diseases while 18,252 patients are Cardiovascular diseases. As demonstrated in Table 4.1 which provides summary descriptive statistics of daily data, the daily average of ED visits is 83.69 (± 28.45) and 26.04 (± 5.68) for Respiratory and Cardiovascular diseases respectively. Seasonal variation is not significant on Cardiovascular diseases with 27 (± 5.78) and 25 (± 5.53) daily average of ED visits in the warm and cold season respectively. However, the daily average of ED visits of Respiratory diseases is much higher in cold season 100 (± 34.18) compared to warm season 62 (± 15.37) which indicated that Temperature could have a great impact on Respiratory diseases. It is worth to mention that SO_2 can be significantly influenced by the change of season. The mean concentration of SO_2 increased from 2.807 to 3.705 at the warm season but decreased to 1.834 at the cold season. The maximum concentration reduced to 38.7 at the cold season from 78.9 at the warm season.

Table 4.1 Summary statistics of daily Hospital ED Visits data, meteorological conditions, and air pollutant concentrations in Coastal Bend.

	Min	1st Qu	Median	Mean	3rd Qu	Max	Sd
Hospital Emergency Admissions							
Respiratory	33	62	79	83.69	102	178	28.45
Cardiovascular	8	22	26	26.04	30	42	5.68
Air Pollutants							
SO_2(ug/m3)	0	0.3	0.7	2.807	2.1	78.9	6.49
Ozone(ug/m3)	0.016	0.027	0.036	0.03775	0.046	0.087	0.01346
$PM_{2.5}$(ug/m3)	0.6	6.5	8.6	9.797	11.75	43.8	5.08
PM_{10}(ug/m3)	6	18	23	25.99	31	69	10.92
Meteorological Parameters							
Temperature (F)	29	65	76	73.27	84	90	12.25
Relative Humidity	44	90	93	91.14	95	100	7.31
Wind Speed	9	16	18	18.46	21	31	4.17
Precipitation	0	0	0	0.03949	0.1	1.22	0.13
Cold Season							
Hospital Emergency Admissions							
Respiratory	48	83.5	100	102.8	120.5	178	24.19
Cardiovascular	8	22	27	26.5	30	42	5.78
Air Pollutants							
SO_2(ug/m3)	0	0.4	0.9	3.705	3.5	78.9	8.00
Ozone(ug/m3)	0.016	0.031	0.037	0.03836	0.044	0.075	0.01015
$PM_{2.5}$(ug/m3)	0.6	6.2	8.1	9.003	11.3	26	4.04
PM_{10}(ug/m3)	9	16.5	20.5	22.29	25.5	68	8.52
Warm Season							
Hospital Emergency Admissions							
Respiratory	33	52	62	63.15	73	118	15.38
Cardiovascular	9	22	25	25.54	29	41	5.53
Air Pollutants							
SO_2(ug/m3)	0	0.3	0.5	1.843	1.3	38.7	4.11
Ozone(ug/m3)	0.016	0.023	0.0325	0.0371	0.048	0.087	0.01627
$PM_{2.5}$(ug/m3)	3.6	6.9	9	10.65	12.35	43.8	5.90
PM_{10}(ug/m3)	6	20	27.5	29.97	39	69	11.80

Note. Min: minimum; 1^{st} Qu: 25^{th} percentile; 3^{rd} Qu: 75^{th} percentile; Sd: standard deviation. Cold season: from November to April; Warm season: from May to October.

Table 4.2 below represents the Pearson correlation coefficient between air pollutants and weather variables. Positive correlations are noted between daily average Temperature and PM_{10} (r = 0.482). Temperature and SO_2 are closely correlated with each other in a negative way (r = -0.334). SO_2 and Ozone levels are negatively correlated with all meteorological variables. $PM_{2.5}$ and PM_{10} Levels are both positively related to Temperature but negatively related to Precipitation. However, $PM_{2.5}$ is positively correlated with Relative Humidity while negative correlation exists between PM_{10} and Relative Humidity.

Table 4.2 Pearson Correlation Coefficients Between Air Pollution and Meteorological Variables

	SO2	Ozone	PM2.5	PM10	T	RH	WS	P
SO_2	1.000							
Ozone	0.244	1.000						
$PM_{2.5}$	-0.073	-0.019	1.000					
PM_{10}	-0.066	-0.021	0.390	1.000				
Average Temperature	-0.334	-0.180	0.321	0.482	1.000			
Relative Humidity	-0.342	-0.266	0.051	-0.074	0.244	1.000		
Wind Speed	-0.197	-0.287	0.071	0.174	0.236	0.051	1.000	
Precipitation	-0.072	-0.091	-0.110	-0.124	-0.077	0.137	0.185	1.000

4.2 STATISTICAL ANALYTICAL RESULTS

Table 4.3 reports the estimates of Cardiovascular and Respiratory diseases daily ED visits with percentage increases of air pollution and meteorological parameters. Exposure to four air pollutants (SO_2, Ozone, $PM_{2.5}$, and PM_{10}) and three meteorological parameters (Temperature, Relative Humidity and Precipitation) results in overall significantly high RR estimates for Respiratory-related mortality. Only two air pollutants ($PM_{2.5}$ and PM_{10}) and the same three meteorological parameters can result in overall significantly high RR estimates for

Cardiovascular-related mortality. This suggests that SO_2 and Ozone posed a higher risk on Respiratory compared to Cardiovascular diseases, with RR = 1.001 (95% CI 1.000-1.002) and RR = 1.619 (95% CI 0.618-4.244) on Respiratory respectively, whereas the RR of these two air pollutants are no more than 1 on Cardiovascular diseases. It is also noticeable that Ozone has the highest risk on Respiratory diseases which is way higher than other explanatory factors.

As for meteorological parameters, the RR of these four variables has similar patterns on both diseases. No significant influence observed on Wind Speed. The RR of Temperature and Relative Humidity on Respiratory diseases (RR = 1.002 (95% CI 1.000-1.003) and RR = 1.000 (95% CI 0.999-1.001)) are just slightly lower than the RR on Cardiovascular diseases with RR = 1.003 (95% CI 1.000-1.006) and RR = 1.001 (95% CI 0.998-1.003)) respectively. But the RR of Precipitation on Respiratory diseases RR = 1.059 (95% CI 0.986-1.137) is a little bit higher than on Cardiovascular diseases RR = 1.002 (95% CI 0.888-1.129).

Table 4.3 Overall RR and 95% CI of mortality due to air pollution and meteorological parameters on Cardiovascular and Respiratory diseases.

	Respiratory			Cardiovascular		
	RR	95% CI		RR	95% CI	
SO_2	1.001	1.000	1.002	0.999	0.996	1.002
Ozone	1.619	0.618	4.244	0.685	0.200	2.345
$PM_{2.5}$	1.001	0.998	1.003	1.001	0.998	1.004
PM_{10}	1.002	1.001	1.004	1.000	0.999	1.002
Temperature	1.002	1.000	1.003	1.003	1.000	1.006
Relative Humidity	1.000	0.999	1.001	1.001	0.998	1.003
Wind Speed	0.997	0.994	0.999	0.997	0.993	1.001
Precipitation	1.059	0.986	1.137	1.002	0.888	1.129

Table 4.4 demonstrates a comparison of the RR on mortality due to air pollution during the cold season (November to April) and warm season (May to October). The most significant difference is that the influence of Ozone peaks at the cold season with RR=3.953 (95% CI 1.067-14.647) compared to warm season RR=0.718 (95% CI 0.186-2.766) which even do not show any risk on Respiratory diseases. The RR of PM_{10} for both diseases decrease to less than 1 on the cold season for both diseases. Ozone and SO_2 have a higher risk in the warm season with RR=1.196 (95% CI 0.183-7.744) and RR=1.004 (95% CI 0.186-2.766) on Cardiovascular diseases while no association is found on the cold season.

Table 4.4 The RR and 95% CI due to air pollution on Cardiovascular and Respiratory diseases for cold season (November to April) and warm season (May to October).

	Respiratory			Cardiovascular		
	RR	95% CI		RR	95% CI	
Cold Season						
SO_2	1.001	0.999	1.002	0.997	0.994	1.000
Ozone	3.953	1.067	14.647	0.442	0.044	4.378
$PM_{2.5}$	1.002	0.998	1.005	1.005	0.999	1.011
PM_{10}	0.999	0.996	1.001	0.995	0.992	0.999
Warm Season						
SO_2	1.002	0.998	1.006	1.004	0.998	1.010
Ozone	0.718	0.186	2.766	1.196	0.183	7.744
$PM_{2.5}$	1.000	0.997	1.003	1.000	0.996	1.004
PM_{10}	1.003	1.001	1.005	1.001	0.999	1.003

Table 4.5 compares the RR of each air pollutant and the RR of that air pollutant after adjusted with other air pollutants. The same pattern is observed as we reported above, all four air pollutants have a significant influence on Respiratory diseases with RR > 1, but only two air pollutants $PM_{2.5}$ and PM_{10} present significant influence on Cardiovascular diseases. The results do not change despite it is in the model that contains only one air pollutant variable or the models that have combined other air pollutant variables. Among all these variables, Ozone remains the highest RR on Respiratory diseases. The RR of Ozone is 2.20726 and increased to 2.35736 after the model was adjusted with $PM_{2.5.}$ But the RR becomes much lower ranging from 1.82882 to 2.09231 after adjusted with other air pollutant variables.

Table 4.5 The RR and 95% CI of mortality due to air pollution on Cardiovascular and Respiratory diseases of models including one variable and models adjusted with other variables.

		Respiratory			Cardiovascular		
		RR	95% CI		RR	95% CI	
SO_2	Without adjustment	1.00103	0.99977	1.00229	0.99777	0.99525	1.00021
	Adjusted for Ozone	1.00083	0.99954	1.00212	0.99795	0.99539	1.00045
	Adjusted for $PM_{2.5}$	1.00105	0.99979	1.00231	0.99778	0.99911	1.00535
	Adjusted for PM_{10}	1.00088	0.99962	1.00214	0.99769	0.99891	1.00227
	Adjusted for Ozone+$PM_{2.5}$	1.00083	0.99954	1.00212	0.99797	0.99541	1.00047
	Adjusted for Ozone+PM_{10}	1.00071	0.99942	1.00201	0.99788	0.99531	1.00038
	Adjusted for $PM_{2.5}$+PM_{10}	1.00090	0.99963	1.00216	0.99774	0.99521	1.00020
	Adjusted for Ozone+ $PM_{2.5}$+ PM_{10}	1.00072	0.99943	1.00202	0.99794	0.99536	1.00044
Ozone	Without adjustment	2.20726	0.92481	5.26810	0.54875	0.17724	1.69129
	Adjusted for SO_2	1.96015	0.80489	4.77354	0.66619	0.20989	2.10601
	Adjusted for $PM_{2.5}$	2.35736	0.98494	5.64213	0.53491	0.17282	1.64829
	Adjusted for PM_{10}	1.92703	0.80539	4.61073	0.53342	0.17175	1.64958
	Adjusted for SO_2+$PM_{2.5}$	2.09231	0.85677	5.10958	0.64823	0.20426	2.04909
	Adjusted for SO_2+PM_{10}	1.74169	0.71378	4.24989	0.64842	0.20391	2.05392
	Adjusted for $PM_{2.5}$+PM_{10}	2.02459	0.84111	4.87324	0.53018	0.17079	1.63885
	Adjusted for SO_2+ $PM_{2.5}$+ PM_{10}	1.82882	0.74525	4.48788	0.64113	0.20169	2.03014
$PM_{2.5}$	Without adjustment	1.00159	0.99948	1.00371	1.00226	0.99913	1.00537
	Adjusted for Ozone	1.00178	0.99966	1.00390	1.00231	0.99918	1.00542
	Adjusted for SO_2	1.00163	0.99951	1.00374	1.00224	0.99911	1.00535
	Adjusted for PM_{10}	1.00088	0.99873	1.00304	1.00220	0.99893	1.00545
	Adjusted for Ozone+ SO_2	1.00178	0.99966	1.00391	1.00228	0.99915	1.00539
	Adjusted for Ozone+PM_{10}	1.00108	0.99891	1.00326	1.00222	0.99895	1.00546
	Adjusted for SO_2+PM_{10}	1.00094	0.99878	1.00310	1.00210	0.99883	1.00535
	Adjusted for Ozone+ SO_2+ PM_{10}	1.00110	0.99892	1.00327	1.00212	0.99885	1.00537
PM_{10}	Without adjustment	1.00249	1.00100	1.00398	1.00045	0.99877	1.00212
	Adjusted for Ozone	1.00238	1.00088	1.00388	1.00053	0.99884	1.00221
	Adjusted for SO_2	1.00241	1.00092	1.00390	1.00059	0.99891	1.00227
	Adjusted for $PM_{2.5}$	1.00236	1.00083	1.00388	1.00011	0.99836	1.00186
	Adjusted for Ozone+ SO_2	1.00233	1.00083	1.00383	1.00063	0.99894	1.00232
	Adjusted for Ozone+$PM_{2.5}$	1.00221	1.00067	1.00374	1.00018	0.99843	1.00194
	Adjusted for SO_2+$PM_{2.5}$	1.00226	1.00074	1.00379	1.00026	0.99850	1.00202
	Adjusted for Ozone+ SO_2+ $PM_{2.5}$	1.00215	1.00062	1.00369	1.00030	0.99854	1.00206

Table 4.6 represents the RR of each meteorological parameters and the RR of that meteorological parameter after adjusted with other meteorological parameters. The Temperature has a significant influence on the morbidity of both Respiratory and Cardiovascular diseases. Also, the RR does not have any significant change after the model was adjusted with other meteorological parameters. The RR of Relative Humidity has the same trend with the RR of Temperature on Cardiovascular. But the trend changes in Respiratory diseases. Relative Humidity itself has a significant impact on Respiratory diseases and the influence remains significant after including Wind Speed or Precipitation or both Wind Speed and Precipitation in the model. But the RR of Relative Humidity decreases to under 1 in the model adjusted with Temperature and any models that included Temperature as the explanatory factor. The RR of Wind Speed (RR < 1) stays the same as we reported in the former model that involved all the air pollution and meteorological parameters. The RR of Precipitation for Respiratory diseases also stays more than 1 in the models containing only weather variables. But the RR of Precipitation decreased to RR=0.97340 (95% CI 0.86773-1.08903) in the model that only considered Precipitation factor. It increases to more than 1 only after the model have added the two variables Temperature and Wind Speed.

Table 4.6 The RR and 95% CI of mortality due to meteorological parameters on Cardiovascular and Respiratory diseases of models including one variable and models adjusted with other variables.

		Respiratory			Cardiovascular		
		RR	95% CI		RR	95% CI	
T	Without adjustment	1.00067	0.99932	1.00204	1.00374	1.00145	1.00604
	Adjusted for RH	1.00071	0.99914	1.00229	1.00308	1.00054	1.00562
	Adjusted for WS	1.00121	0.99980	1.00263	1.00434	1.00194	1.00676
	Adjusted for P	1.00070	0.99934	1.00207	1.00372	1.00142	1.00603
	Adjusted for RH+WS	1.00137	0.99973	1.00301	1.00375	1.00106	1.00645
	Adjusted for RH+P	1.00078	0.99918	1.00238	1.00300	1.00043	1.00558
	Adjusted for WS+P	1.00134	0.99991	1.00277	1.00439	1.00195	1.00684
	Adjusted for RH+WS+P	1.00162	0.99993	1.00330	1.00375	1.00098	1.00653
RH	Without adjustment	1.00024	0.99909	1.00139	1.00257	1.00051	1.00465
	Adjusted for T	0.99993	0.99860	1.00127	1.00137	0.99909	1.00367
	Adjusted for WS	1.00032	0.99917	1.00148	1.00258	1.00052	1.00467
	Adjusted for P	1.00022	0.99906	1.00138	1.00267	1.00059	1.00477
	Adjusted for T+WS	0.99975	0.99841	1.00110	1.00113	0.99884	1.00346
	Adjusted for T+P	0.99987	0.99852	1.00123	1.00145	0.99914	1.00379
	Adjusted for WS+P	1.00027	0.99911	1.00144	1.00266	1.00059	1.00476
	Adjusted for T+WS+P	0.99958	0.99821	1.00095	1.00113	0.99878	1.00351
WS	Without adjustment	0.99746	0.99542	0.99951	0.99890	0.99530	1.00250
	Adjusted for RH	0.99742	0.99538	0.99948	0.99883	0.99522	1.00243
	Adjusted for T	0.99696	0.99484	0.99909	0.99684	0.99306	1.00062
	Adjusted for P	0.99726	0.99517	0.99935	0.99903	0.99536	1.00270
	Adjusted for RH+T	0.99693	0.99479	0.99907	0.99709	0.99328	1.00091
	Adjusted for RH+P	0.99724	0.99514	0.99934	0.99906	0.99539	1.00274
	Adjusted for T+P	0.99665	0.99446	0.99885	0.99674	0.99286	1.00063
	Adjusted for RH+T+P	0.99655	0.99434	0.99877	0.99709	0.99314	1.00104
P	Without adjustment	1.01328	0.94762	1.08349	0.97340	0.86773	1.08903
	Adjusted for RH	1.01189	0.94588	1.08250	0.95631	0.85169	1.07094
	Adjusted for WS	1.03255	0.96410	1.10586	0.97910	0.87102	1.09772
	Adjusted for T	1.01613	0.95001	1.08686	0.99065	0.88271	1.10885
	Adjusted for RH+WS	1.03090	0.96218	1.10454	0.96173	0.85476	1.07929
	Adjusted for RH+T	1.01726	0.95001	1.08927	0.97786	0.86962	1.09670
	Adjusted for WS+T	1.04239	0.97253	1.11728	1.01324	0.90015	1.13762
	Adjusted for RH+WS+T	1.04702	0.97537	1.12394	1.00062	0.88634	1.12681

4.3 LAG DAY EFFECT

To provide a better interpretation and comparability of the influence of each variable, we examined their lag structure. The overall effect for an increase of 10 μg/m3 in SO_2, PM_{10}, $PM_{2.5}$, 0.01 μg/m3 in Ozone and 10 unit in Temperature, Relative Humidity, Wind Speed, 0.01 unit in Precipitation over 7 days of delay, together with its 95% confidence intervals for Cardiovascular and Respiratory diseases are presented in figure 4.1 and 4.2. It is obviously observed that the RR for all variables do not always stay at the same level during lag days. For example, there is no association between SO_2 and Cardiovascular diseases on the current day that patients are exposed to SO_2, but significant influence of SO_2 on Cardiovascular diseases are found on the third and fourth delayed day with a relative risk higher than 1. In contrast, the relative risk of Relative Humidity on Cardiovascular diseases from lag 0 to lag 2 days are significant while no association are found at the third and fourth delayed day.

For Cardiovascular diseases mortality, the association is found on the current exposed day of $PM_{2.5}$, Ozone, Temperature, and Relative Humidity factors. But the largest relative risk of $PM_{2.5}$ and Ozone are on lag 4 day, the largest RR of SO2, Ozone, and Temperature are observed on lag 3 days, and for Relative Humidity, Wind Speed and Precipitation it is on the lag 2 days.

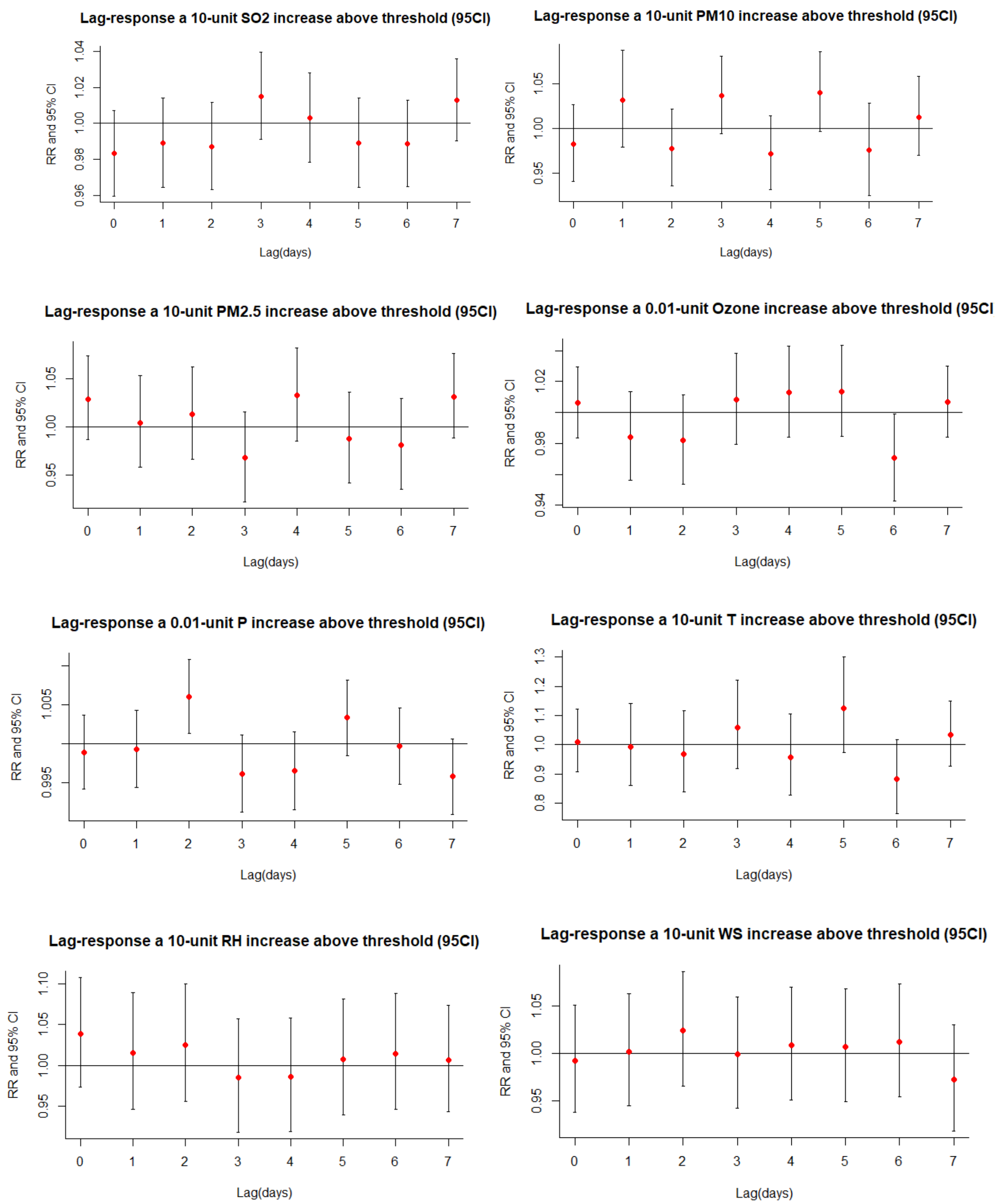


Figure 4.1 RR and 95% CI of Cardiovascular mortality associated with 10 or 0.01 unit increase of air pollutant and meteorological parameters over 7 days.

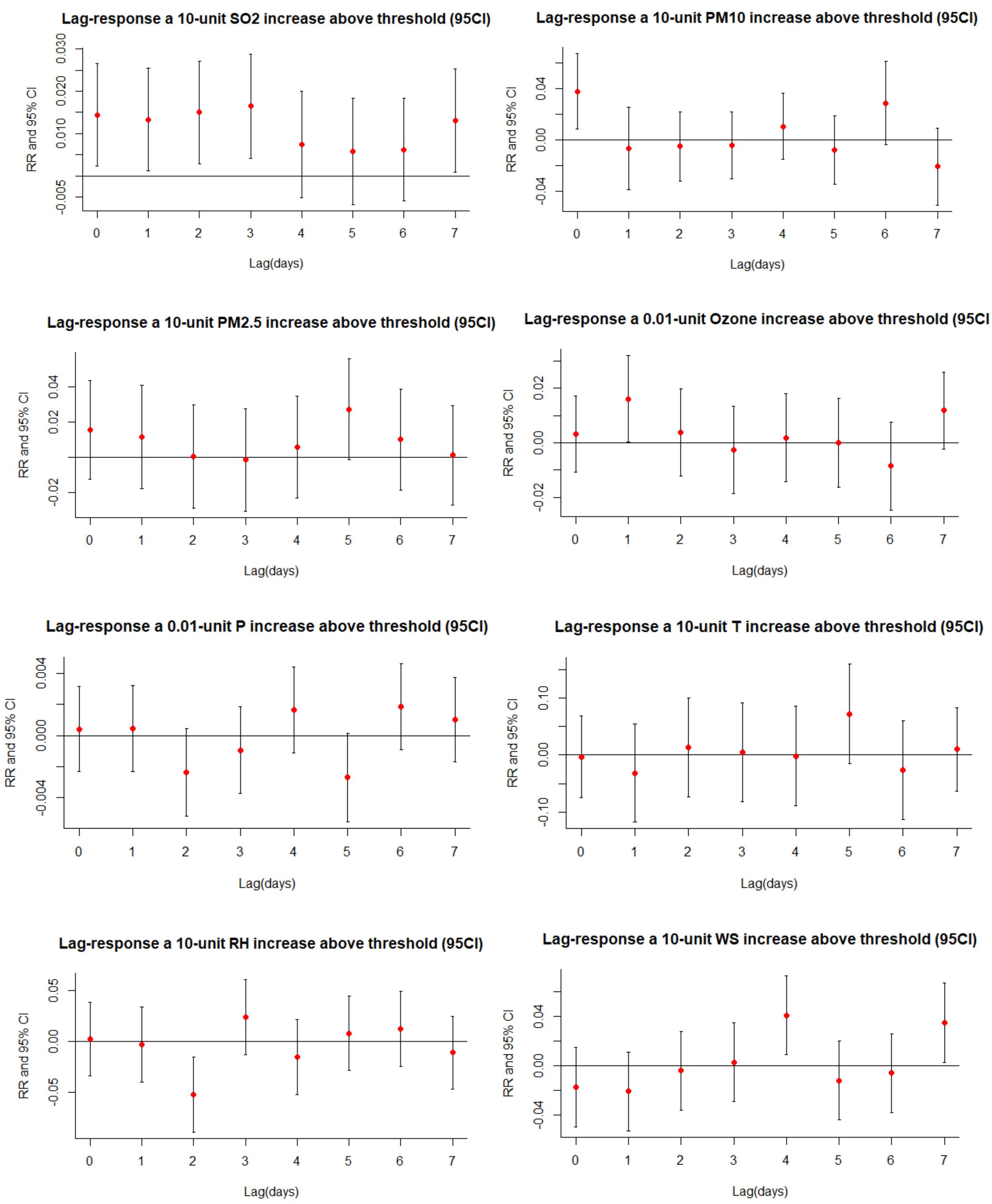
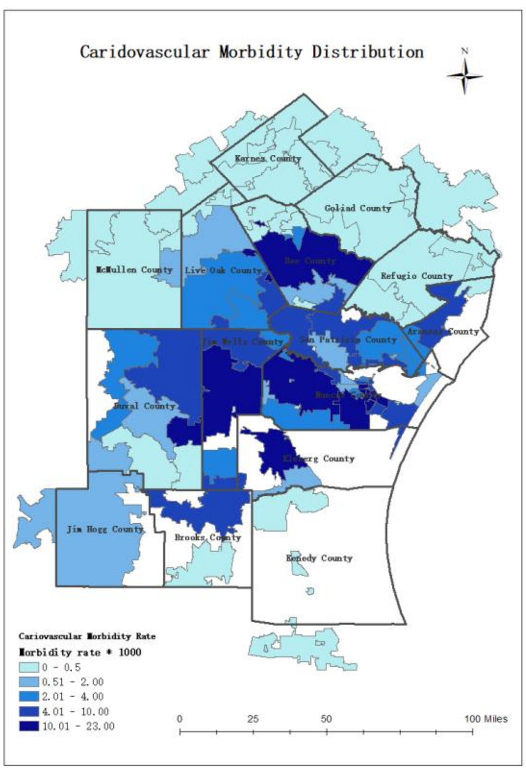


Figure 4.2 RR and 95% CI of Respiratory mortality associated with 10 or 0.01 unit increase of air pollutant and meteorological parameters over 7 days.

4.4 SPATIAL DISTRIBUTION

4.4.1 General Distribution

There is a total of 58,665 patients diagnosed as Respiratory diseases and 18,252 patients diagnosed as Cardiovascular diseases from 2010 to 2012 in the 15 Coastal Bend counties. The ED visits ratio which calculates the rate of ED visits on the population within each zipcode is generated here for the spatial analysis. For both Cardiovascular and Respiratory diseases, the ED visits ratio are mainly concentrated in Nueces county and extended to adjacent counties like San Patricio, Jim Wells, and Kleberg. The adjacent part of Aransas, Bee, Live Oak, Brooks and Duval counties also represented high morbidity concentration. While low morbidity rate has been observed in the north part of the study area in McMullen, Refugio, Karnes, Kenedy, and Goliad counties. The spatial distribution of these two diseases are shown below:



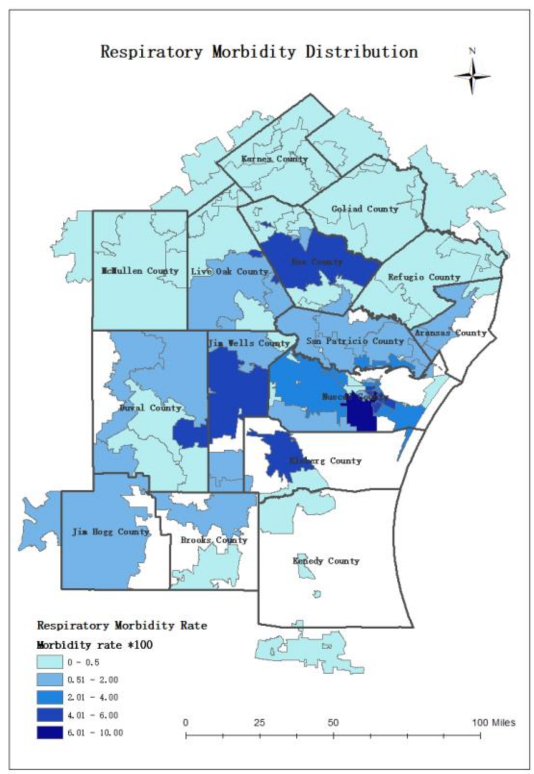


Figure 4.3 Cardiovascular Morbidity Distribution. Figure 4.4 Respiratory Morbidity Distribution.

4.4.2 Spatial Autocorrelation and Hotspot Analysis

In the spatial autocorrelation analysis, the reported z-score of 7.638551 and 9.489486 for Cardiovascular and Respiratory diseases indicate that there is less than 1% likelihood that the clustered pattern could be the result of random chance.

Furthermore, the hotspot analysis results show in Figure 4.5 and 4.6 provide strong evidence to support the cluster pattern. Cardiovascular and Respiratory have a similar hot spot and cold spot pattern in the study area. They both concentrates in Nueces, San Patricio, and Kleberg counties and small areas in the neighboring counties. Nueces County has the most intense cluster pattern observed. Jim Wells and the southeast part of Duval counties also shows a concentrated pattern for Cardiovascular diseases, but the concentration is not intense. The cold spot is found in Karnes County and the north part of Mcmullen, Bee and Live Oak counties. A small area in the middle of Goliad counties also shows a cold spot for Cardiovascular diseases. As for the rest part of the study area, there is no significant pattern found.

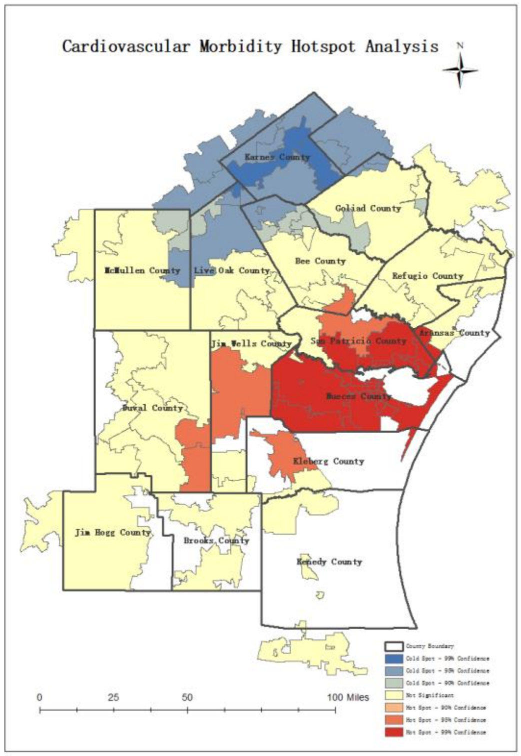


Figure 4.5 Cardiovascular diseases hot spot and cold spot.

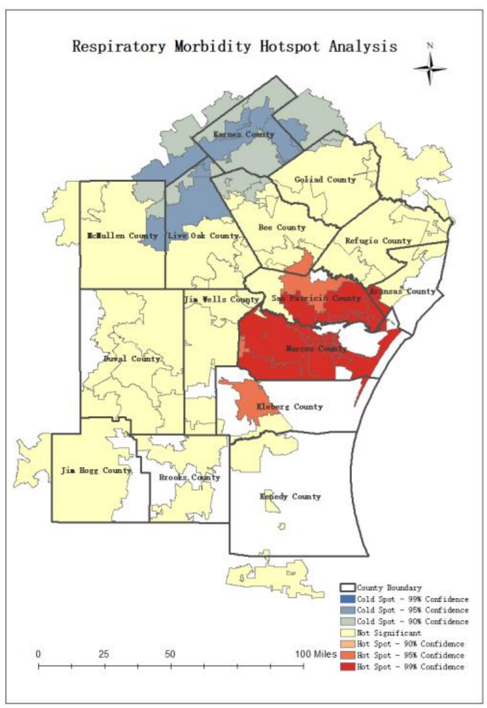


Figure 4.6 Respiratory diseases hot spot and cold spot.

4.5. SPATIAL VARIATION

The results of spatial variation are presented in Table 4.6. The RR of mortality due to meteorological parameters on Cardiovascular and Respiratory Diseases for the whole study area is the same as we analyzed in section 4.2.

For Cardiovascular diseases, Wind Speed does not have a significant influence on the morbidity no matter it is for the whole study area or for any of the three sub-areas. The opposite situation is observed on Temperature, it presents high RR within each sub-area or at the whole study area with just slightly change. As for the whole study area, Relative Humidity and Precipitation both have a significant influence on Cardiovascular morbidity. But the influence varies when it comes to sub-areas, Relative Humidity has high RR in subarea 1 and subarea 2 while Precipitation only presents significant influence in subarea 3 with RR= 1.0340315 (95% CI 0.882149 - 1.195497).

For Respiratory diseases, only Temperature and Precipitation have a significant impact with RR > 1. The same trend is observed in subarea 1 and subarea 2. The influence of Temperature increases slightly from the original RR = 1.0016 to RR = 1.002 in these two sub areas. The RR of Precipitation decreases from RR = 1.04 to RR = 1.02 in subarea 1 but increases to RR = 1.11 in subarea 2 which indicates that Precipitation has a more significant influence in subarea 2. The influence of Relative Humidity, Wind Speed and Precipitation in subarea 3 stays the same with the RR in the whole study area. But the RR of Temperature decreases from significant to insignificant with RR= 0.999223 (95% CI 0.9952018 - 1.003261).

Table 4.7 The RR and 95% CI of mortality due to meteorological parameters on Cardiovascular and Respiratory diseases of the whole study area and three sub-areas.

	Respiratory			Cardiovascular		
	RR	95% CI		RR	95% CI	
Study Area						
Temperature	1.00161610	0.99993070	1.00330440	1.00374890	1.00098070	1.00653410
Relative Humidity	0.99957540	0.99820590	1.00094680	1.00113080	0.99877910	1.00351020
Wind Speed	0.99655470	0.99434058	0.99877380	0.99708950	0.99314100	1.00104390
Precipitation	1.04702250	0.97536517	1.12394420	1.00061820	0.88633590	1.12680740
Sub-area1						
Temperature	1.002236	1.0002721	1.0042044	1.0030486	0.99961	1.00651400
Relative Humidity	0.99923	0.9975891	1.00087370	1.0004144	0.997452	1.0034167
Wind Speed	0.996892	0.9944798	0.99931000	0.9969017	0.99239	1.00141930
Precipitation	1.020556	0.9430753	1.10440320	0.9677451	0.83514370	1.11581800
Sub-area2						
Temperature	1.002085	0.9984400	1.0057428	1.0040114	0.99853	1.009567
Relative Humidity	0.999297	0.9965174	1.0020843	1.0042507	0.999919	1.008701
Wind Speed	0.99625	0.9908604	1.001668	0.9983569	0.989971	1.006775
Precipitation	1.113455	0.9580089	1.2941245	0.962094	0.733449	1.235101
Sub-area3						
Temperature	0.999223	0.9952018	1.003261	1.0076671	1.000584	1.014841
Relative Humidity	0.99829	0.9951896	1.0013996	0.9975847	0.99235	1.002981
Wind Speed	0.996062	0.9897946	1.002369	0.9969589	0.985925	1.008041
Precipitation	1.042998	0.9571891	1.1364986	1.0340315	0.882149	1.195497

CHAPTER V: DISCUSSION AND CONCLUSION

5.1. DISCUSSION

This time-series study of ED visits provide an opportunity to explore the influence of air pollution levels and weather conditions on Cardiovascular and Respiratory diseases. According to this study, air pollutions and meteorological parameters are relatively associated with both Cardiovascular and Respiratory diseases ED visits in Coastal Bend area.

For Cardiovascular diseases, $PM_{2.5}$ and PM_{10} in air pollutants as well as Temperature, Relative Humidity and Precipitation among meteorological parameters can pose threat to Cardiovascular diseases in the study area. Our findings are consistent with the results reported by existing studies. As a study reported, $PM_{2.5}$ increase the relative risk of acute Cardiovascular events by 1% to 3% within a few days (Rajagopalan, S., et al., 2018). Similar findings have been reported in the United States in the National Institutes of Health–AARP cohort (N = 517,043), in which exposure to $PM_{2.5}$ increase Cardiovascular diseases mortality by a relative 10% (per 10 μg/m3), despite the $PM_{2.5}$ levels is low(10 to 13 μg/m^3) (Weichenthal, S., et al., 2014). $PM_{2.5}$ and PM_{10} have significant higher risk on Cardiovascular diseases in a European study where most hazard ratios for the association of air pollutants with mortality from overall Cardiovascular diseases and with specific Cardiovascular diseases were approximately 1.0, with the exception that the hazard ratio for $PM_{2.5}$ is as high as RR = 1.21 (95% confidence interval = 0.87-1.69) per 5 μg/m and for PM_{10}, the ratio is 1.22 (0.91-1.63) per 10 μg/m (Beelen, R., et al., 2014). In some studies, PM_{10}, SO_2 and NO_2 are the major air pollutants that have been investigated and confirmed to have associations with Cardiovascular diseases (Zhang, C., et al., 2017; Çapraz, Ö., et al., 2016). However, the data of NO_2 are not available in the Coastal Bend area, thus limiting the evaluation of the influences of NO_2 on ED visits. The impact of SO_2 and Ozone on Cardiovascular diseases are not significant in this study, similar to the study in Iran which did not have significant influence observed on SO_2 and Ozone while CO, NO_2, and PM_{10} were found as trigger facotrs (Soleimani, Z., et al., 2015). Another interesting finding in this study is that SO_2 shows significant influence on Cardiovascular diseases only during warm season when the concentration level is much lower than the average level. It is possible to be explained that SO_2 only causes risk on Cardiovascular diseases at low rate in this study area. The hypothesis that Temperature is the most significant trigger among meteorological parameters have been supported by many studies (Tsangari, H., et al., 2016; Alfésio L. F., et al., 2002; Grass, D., & Cane, M. 2008). According to our study, Relative Humidity and Precipitation are also likely to be positively correlated with the Cardiovascular morbidity rates in Coastal Bend. However, as a study mentioned, complex relationships exist between ambient air pollution and meteorological factors, their covariance can result in a high likelihood that the effect of one variable could modify the effect of the other (Jennifer et al., 2014). Therefore, it is possible that the change in weather conditions can cause an impact on air pollution concentration. Consequently, the morbidity increases or decreases to some extent. Further study needs to be done before we can make any assessment at this stage.

As for Respiratory diseases, air pollution seems to have greater impact on it. The increases of SO_2, Ozone, $PM_{2.5}$ and PM_{10} were all confirmed to have threat on Respiratory morbidity. In addition, the relative risk of Ozone in the cold season is surprisingly high whereas no significant association was found in the warm season. The results in our study are consistent with previous studies. In a study undertaken in the UK, there was a very strong positive association between all Respiratory admissions with SO_2, weak positive associations with PM_{10}, $PM_{2.5}$ (Anderson et al., 2001). A study in Miland identified a positive association between emergency admissions for Respiratory diseases and ambient exposure to pollutants such as PM_{10}, O_3, CO and SO_2 (Santus, P., et al., 2012). The influence of meteorological parameters have the same trend as we observed in our investigation of Cardiovascular diseases.

5.2. CONCLUSION

Our results in this time-series study supported our hypothesis. Exposure to higher concentrations of air pollutants (SO_2, Ozone, $PM_{2.5}$, and PM_{10}) results in overall significantly high RR for Respiratory-related mortality. Among all the air pollutant, Ozone and SO_2 do not have a significant influence observed on Cardiovascular diseases. The influence of air pollutants on morbidity change by season and by the combination with other air pollutants. Ozone levels have a significant strong association with Respiratory diseases in the cold season, but no association is found between these two in the warm season. SO_2 become harmful during the warm season on Cardiovascular diseases. In addition, the risk of each air pollutants varies slightly when the model accounts for single pollutant or multiple pollutants, but the overall results remain the same.

According to our study, Temperature, Relative Humidity and Precipitation have a higher risk of Cardiovascular and Respiratory diseases, while Wind Speed shows no significant association with these two diseases. The influence of the three meteorological parameters changes slightly after the model has considered other variables. The risk of Relative Humidity became not significant on Respiratory diseases after Temperature is accounted for in the model. Besides, Precipitation only presents an association with Cardiovascular morbidity after adjusted for Wind Speed and Temperature.

The cluster pattern of Cardiovascular and Respiratory diseases is supported. At the meantime, the spatial variance is identified in this study. According to this study, the overall pattern and trend of ED visit data for Cardiovascular and Respiratory diseases are significantly clustered. They both concentrated in Nueces, San Patricio, and Kleberg counties and small areas in the neighboring counties. Temperature does not have associations with the Respiratory morbidity in sub-area 3 while the significant strong associations are found in sub-area 1 and sub-area 2. In sub-area 1 and sub-area 2, Precipitation does not have a significant influence on Cardiovascular diseases. Furthermore, in sub-area 3, Relative Humidity does not show the influence on Cardiovascular morbidity.

Through the model assessments, it is possible to conclude that air pollution and meteorological parameters are important factors affecting the morbidity of Cardiovascular and Respiratory diseases in Coastal Bend areas during October 1, 2010, to August 31, 2012. We hope that these findings may have implications for local hospitalization prevention policies.

5.3 LIMITATIONS

There are several limitations within this study while the most important one is from data. Air pollution data are only provided with the stations located within Corpus Christi area. These data are adopted in this study for the whole Coastal Bend area. It can be possible that for areas not close to Corpus Christi, the air pollution level might be different from the data we can obtain. After all, not all areas have refineries which might impact air qualities. In addition, air pollution data like NO_2, CO are also important factors that have been found to have significant influence on the ED visits of Cardiovascular and Respiratory diseases in many studies. However, we do not have daily NO_2, CO information provided in Coastal Bend area, therefore we are not able to get these two factors involved in this study.

Hospitalization data adopted in this study is the data that have been processed and filtered from the original data. The data that missing zip code or discharge date are not incorporated to this study. In addition, the Cardiovascular and Respiratory ED visits data are selected based on the ICD-9 code which is converted from ICD-10 code. Since the two codes have totally different rules, it might be possible that some code belongs to Cardiovascular or Respiratory are neglected or some other diseases are included in the conversion code. Slightly data loss could happen during these processing steps.

The small size of the study area is also a limitation in terms of spatial analysis variation analysis. Due to the only few air pollution stations in this area, it is not able to study the effect of air pollution on Cardiovascular and Respiratory diseases spatially.

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