Associations Between Exposure To Air Pollution After A Dust Event And Hospitalizations.

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ASSOCIATIONS BETWEEN EXPOSURE TO AIR POLLUTION AFTER A DUST EVENT AND HOSPITALIZATIONS.

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Dedication

Dedicated to my wonderful and deeply missed Mother Luz Maria Cuellar Ayala (1936-2017) and my Father Donato Molina Razo (1934-2017), may they rest in peace. My wonderful parents taught me that with God’s direction, love, hard work and perseverance, we can succeed in life. My dad had Alzheimer’s disease and knowing the pain of what families go through and the terrible feeling the patient must have, I also dedicate this work to those patients, families and caregivers who wish a cure is nearby.

Love you and miss you so much!
ASSOCIATIONS BETWEEN EXPOSURE TO AIR POLLUTION AFTER A DUST EVENT AND HOSPITALIZATIONS.

by

ESTRELLA DE JESUS HERRERA-MOLINA, MS.

DISSERTATION

Presented to the Faculty of the Graduate School of
The University of Texas at El Paso
in Partial Fulfillment
of the Requirements
for the Degree of

DOCTOR OF PHILOSOPHY

Environmental Science and Engineering Program
THE UNIVERSITY OF TEXAS AT EL PASO
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Abstract

The Southwestern region has been identified as one of the most persistent dust producing regions of North America. Exposure to inhalable particulate matter (PM$_{10}$) originating from desertic landscape during dust events / dust exposures (DEs) can reach hazardous levels. El Paso, Texas’s ambient air has reached hazardous levels of PM$_{10}$ above 4000 $\mu$g/m$^3$ with near zero visibility due to these natural events. There are very few prior studies in the southwestern United States pertaining to the associations between exposure to atmospheric aerosol after DEs and hospitalizations, nor are there many epidemiological studies globally in dusty environments where most of the atmospheric aerosol is soil derived. Therefore, the relationship between dust exposure and hospital admissions due to neurodegenerative diseases (ND), mental illness (MI), Valley fever (VF), Asthma, Coronary Atherosclerosis, Associated Diseases (AD), and ICD-9 category and the modifying effect of the demographic factors (age, income and education attainment) was assessed at the County of El Paso, TX.

A conceptual model with all predictive and response variables with model equations was performed to analyze most factors influencing hospitalizations during DE in El Paso. The predictive model was able to describe factors related to hospitalization during blowing dust events and to predict future hospitalization rates based on dust events. This model analysis may be applied using data mining in other arid locations. Descriptive data results showed that from 2010-2014 there were more hospitalizations in a DE (62%) than in a regular day (RD) (38%). During DE there was a factor of 11.38% more hospitalizations due to acute conditions; 11.81% more from chronic conditions and 1.53% more from mental health than in a regular day.

An intelligent tool was developed using Case-based Algorithm based on Ant Colony Algorithm and the programming language Java (J2SE). Proposed algorithm helps to improve the
ambulance routing demand by 35% of cases during and after a DE in El Paso County. Using Bluetooth, it is possible to use our proposed model of ambulances in an emergency related to a severe dust storm. In addition, a Kriging Model of incidence with birth cases (single liveborn, delivered by cesarean section) was performed, and shows that in the predicted future of increasing dust storms there will be a necessity of more ambulances to transport more patients during a dust event.

Using a Poisson regression, it was found that the relative risk of hospitalizations due to VF, coronary atherosclerosis, genitourinary diseases, ND, injury and poisoning, circulatory system conditions, respiratory system diseases, births, septicemia, AD and all ICD-9 admissions were significantly positively associated with DE (through increases of at least 100 micrograms per cubic meter of daily maximum hourly PM$_{10}$, and/or increases of at least 10 mph in daily hourly average wind speed in El Paso, Texas between 2010 and 2014, at different lag periods after exposure, indicated from higher to lower significant risk. Patients with medium and low socio-economic status showed a significant need to pay for their chemotherapy services; circulatory system conditions; aftercare services; and injury and poisoning associated with a DE. As age decreases, the chances of a patient being hospitalized due to AD after a DE increases.

Recommendations for reduction of outdoor and indoor exposures to DE should be generated for El Paso County. Public policies and individual actions are essential to reduce the human health effects of DE. Due to forecasts that suggest DE will continue to rise an additional urgency of public policies to reduce DEs need to be taken, such as physical wind erosion control measures such as paving roads and reforestation. Individual actions need to be taken e.g., avoiding outdoor activities, wearing a mask and eye coverings during a DE, improving household insulation, and raising an environmental conscience.
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DATE: August 8, 2016

TO: Estrella Herrera, M.S.

FROM: University of Texas at El Paso IRB

STUDY TITLE: [939896-1] Associations between exposure to air pollution, and the incidence of cardiovascular and respiratory diseases in El Paso Metropolitan area.

IRB REFERENCE #: College of Engineering

SUBMISSION TYPE: New Project

ACTION: DETERMINATION OF EXEMPT STATUS

DECISION DATE: August 8, 2016

REVIEW CATEGORY: 45 CFR 46.101(b)(4)

Thank you for your submission of New Project materials for this research study. University of Texas at El Paso IRB has determined this project is EXEMPT FROM IRB REVIEW according to federal regulations.

Your study has received approval at UTEP but may require further review and approval from the institutions listed in your application. Please verify with their IRB prior to engaging in research. Please ensure to forward a copy of all IRB approval letters to the UTEP IRB office.

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We will put a copy of this correspondence on file in our office.

If you have any questions, please contact the IRB Office at (915) 747-8841 or irb.orsp@utep.edu. Please include your study title and reference number in all correspondence with this office.

cc:
Chapter 1: Introduction

Dust Storms and Particulate Matter

In southwest North America, dust storm frequency is increasing (Tong et al., 2017) and the seasonality of dust events is changing (Hand et al., 2016). Hand et al. (2016), based on their springtime trend analyses at southwestern USA, indicate that regional mean PM$_{2.5}$ (particulate matter with mean aerodynamic diameter smaller than 2.5 micrometers) dust concentrations have increased 5.4% per year ($p<0.01$) from 1995 to 2014, especially in March, reflecting in an earlier onset of the spring dust season by 1 to 2 weeks over the 20-year time period from 1995 to 2014. In addition, Tong et al. (2017), report a “direct evidence of rapid intensification of dust storm activity over American deserts in the past decades (1988–2011)”. They estimate that the frequency of windblown dust storms has increased 240% from 1990s to 2000s and with it the infection rate of Valley fever, a dust-related disease, increased 800% from 2000 to 2011.

My study focuses on El Paso, Texas, the largest city in the U.S. portion of the Chihuahuan Desert. The northern Chihuahuan Desert is the one of the most significant sources of dust in the Western Hemisphere (Lee et al., 2009; Novlan et al. 2007; Prospero et al., 2002). The high frequency of dust events (DE) in these regions are associated with large-scale dry climate (climate type -according to the Köppen climate classification system- hot desert (BWh)) (Lee et al., 2012). In this region, agricultural lands, ephemeral lakes, and dry riverbeds have been identified as the main sources of the dust from this desert that is blown into El Paso, Texas (Lee et al., 2009 & Rivera Rivera et al., 2010). In El Paso, dust events have been identified as important environmental hazards (Lee et al., 2009 & Novlan et al., 2007). Based on data collected at the El Paso International Airport from 1932 through 2005, dust events in El Paso occur on average 15 times a year and last an average of 2 hours each (Novlan et al., 2007). In this region, dust events occur most commonly
during the months of December through May when ambient air is dry and winds can reach high
speeds (>25 mph), blowing primarily from the westerly and southwesterly directions (Novlan et
al., 2007). At wind speeds greater than 25 mph, dust can be raised into the atmosphere and/or
transported for long distances by synoptic-scale weather systems (horizontal length scale of the
order of 1000 kilometers or more), which results in widespread exposure to ambient air particle
mixtures (Lee et al., 2009). High wind speed indicates the predominance of coarse particles and
can be used as a surrogate variable for the PM$_{10}$ (particulate matter with mean aerodynamic
diameter smaller than 10 micrometers) dust in El Paso (Staniswalis et al., 2005).

Poor visibility is a side effect of dust events. Visibility can easily be reduced from 0 to 3
miles with PM$_{10}$ >140 μg/m$^3$ and wind speed >10 mph. For example, on January 16$^{th}$ of 2012, the
visibility was reduced to 1.3 miles with a wind speed of 14.8 mph, and PM$_{10}$ of 141.1 μg/m$^3$. Flight
delays, closed roads and difficulty to recognize distant objects by unaided eye beyond 0-3 miles
(depending on the severeness of low visibility) such as distant buildings, trees, hills, incoming
traffic are some effects of low visibility. During such conditions the sky looks brownish (Horvath,
1998).

**Health Effects**

The major sources of inorganic particulate matter (PM) in the dry region of Texas even on
non-dusty days are fugitive dust from unprotected surfaces, including geologic materials from the
surrounding desert and unpaved roads, and include trace elements from re-suspension of deposited
metals previously emitted from several regional point sources (Gill et al., 2009 & Van Pelt &
Zobeck, 2007). An example of point sources of anthropogenic aerosols in the region are petroleum
refineries within this study area. Petroleum refineries are documented in many cases as having
serious adverse effects to the land and population’s health (Oil Change International, 2018). Air
toxins emitted from petroleum refining (La, Na, K, V, Ni, Co, Cu, Zn, Ga, As, Se, Mo, Cd, Sn, Sb, Ba, W, and Pb) (Bozlaker et al., 2017) can cause cancer, birth defects, chronic conditions like asthma (EPA, 2018) and damages in learning and memory to populations exposed to these elements (Bozlaker et al., 2017). Furthermore, Khan and Strand (2018) showed that road dust elements most frequently referenced in articles are Pb, platinum-group elements (Pt, Rh, and Pd), Al, Zn, V, and polycyclic aromatic hydrocarbons which have harmful effects.

Much less is known about the overall health effects of atmospheric aerosol particles during a DE compared to the thousands of studies of urban, industrial, and traffic-derived PM health effects (Morman & Plumlee, 2014). In recent years, an increasing trend has been observed in the number of studies investigating the associations of blowing dust events on human health, specifically the inorganic aerosol particles that are of desert origin which have in common an inflammatory response pathway from the body. One of the associations is the relationship of hospital admissions during dust storms to cardiovascular disease (Al et al., 2018; Behzad et al., 2018; Ebrahimi et al., 2014; Khaniabadi et al., 2017; Morman et al., 2013), respiratory diseases (Schweitzer et al., 2018; Yu et al., 2012) and diabetes (Chan et al., 2018), but fewer on mental health and other diseases. Studies on this subject are being mostly done in Asia and Middle East (Al et al., 2018; Behzad et al., 2018; Chan et al., 2018; Ebrahimi et al., 2014; Khaniabadi et al., 2017; Morman et al., 2013; Schweitzer et al., 2018; Yu et al., 2012) which have reported significant associations.

Al et al. (2018) investigated the effects of desert dust storms and climatological factors on mortality and morbidity of cardiovascular diseases in patients admitted to emergency department in Gaziantep, Turkey. They concluded that acute coronary syndrome (ACS) was increased by the presence of dust storms, PM$_{10}$ elevation, and maximum temperature. Ebrahimi et al. (2014)’s
findings showed a significant increase in emergency admissions for cardiovascular and respiratory diseases during dust storms in Sanandaj, Iran. Khaniabadi et al. (2017) studied hospital admissions in Iran for cardiovascular and respiratory diseases attributed to dust storms and demonstrated a significant impact of air pollution on people. Kanatani et al. (2010) found that desert dust exposure is associated with increased risk of asthma hospitalization in children in Toyama, Japan. Chan et al. (2018)’s study showed that Asian dust storms were positively associated with diabetes hospital admissions for women. Studies by Keil et al. (2016 a & b) reviewed the health effects from exposure to atmospheric mineral dust near Las Vegas, NV, USA. They found that brain CD3+ T cells and natural killer cell activity were significantly reduced and suggested that dust from this area may present a potential health risk.

The main mineral component of dust is silica or Silicon Dioxide (SiO$_2$). Liu et al. (2017) showed that exposure to silica as respirable dust has potential adverse effects on the blood-brain barrier (BBB) -which serves as a barrier between the central nervous system (CNS) and the peripheral circulation. The brain tissue has very limited regenerative capacity which is a reason why it is protected by the BBB. The BBB serves as a natural barrier between the central nervous system (CNS) and the peripheral circulation and maintains the brain homoeostasis and neuronal microenvironment. It consists of a vascular structure of brain micro vessel endothelial cells (BMECs) coupled with astrocytes and pericytes in the brain (Disdier et al., 2015). It is demonstrated that SiO$_2$ passes through the BBB structure and induces inflammation by reactive oxygen species (ROS) and Rho-kinase (ROCK) pathways (Schreibelt et al., 2007). Silica also activates IL-1B secretion in human macrophages analyzed in media supernatants (SN) and in cell extracts (Cell) (Figure 1.1) (Dostert et al., 2008).
Figure 1.1 Silica activates IL-1B secretion in human macrophages. Analyzed in media supernatants (SN) and in cell extracts (Cell). From Dostert et al. (2008)

This systemic inflammation could explain why silica dust (mostly present in dust events) shows effect on brain function (Sharma et al., 2009); decreases the number of brain CD3+ T cells after dust exposure with silica and heavy metals present in the southwest USA soil (Keil et al., 2016); reduces the immune response with PM of 4.6, 3.1, and 4.4 μm at the southwest USA (Keil et al., 2018); passes across the placental barrier and enters fetal liver and brain (Yamashita et al., 2011); had adverse mental health outcomes in retired factory workers (Jiang et al., 2014); incremented epithelial permeability in patients with silicosis who smoke (Nery et al., 1993); was associated with diabetes in women after exposed to Asian Dust Storms (ADS) (Chan et al., 2018); and increased hospitalizations during DEs for expected causes such as respiratory and cardiovascular disorders (Khaniabadi et al., 2017; Yu et al., 2012). In addition, a combination of SiO₂ exposure with several adverse factors such as hypertension, stress, and environmental toxicants could aggravate brain pathology and induce cerebrovascular toxicity by increasing pro-inflammatory responses and disturbing the BBB integrity (Sharma et al., 2013; Zhang et al., 2012).

In summary, Zhang et al. (2016) did a systematic review of global desert dust and associated human health effects (Figure 1.2), stating that “many study results suggest that the
allergic inflammation aggravated by desert mineral dust may be due to mineral elements (mainly SiO₂) and that “it is widely accepted that desert dust has the capacity to (1) cause damage to the alveolar walls and bronchial epithelial cells through a direct physical effect; (2) influence oxidative stress and release of pro-inflammatory cytokines in respiratory epithelial cells; (3) damage DNA (the organic compounds and the insoluble particle-core might be the main contributors to DNA damage); and (4) cause a deterioration in pulmonary function”.

Figure 1.2 Systemic inflammation mechanism due to desert dust. Diagram shows how desert dusts affect the respiratory and immune systems by causing a direct effect to the alveolar walls and epithelial cells; by influencing the oxidative stress; and release of pro-inflammatory cytokines. From Zhang et al., 2016.

Studies on DE health effects completed in the Chihuahuan Desert are very limited in number despite the abundance of dust storms in this geographical location. Rodopoulou et al. (2014) studied the associations of ambient particulate matter and ozone with hospital emergency room and admissions for respiratory and cardiovascular visits in adults in Dona Ana, NM. However, they did not specifically study the associations of natural PM during blowing dust events and the effects of PM on other diseases. Another analysis by Grineski et al. (2011) studied the
hospital admissions for asthma and acute bronchitis and if age, sex, and insurance status modified the effects of dust and low wind events in El Paso, Texas. They found that dust and low wind events were associated with increased chances of hospitalization for asthma and bronchitis amongst all ages and adults. Adults covered by Medicaid and without health insurance had higher risks of hospitalization for asthma and acute bronchitis.

**Optimization of Ambulances Via Algorithms**

Understanding if individuals are vulnerable to the effects of extremely high exposure to desert-originated PM during DEs is relevant for the communities living in the southwestern U.S., as well as for other similar areas where dust storms are common, and the need of efficient ambulance routes is essential (Mohammad et al., 2017). It is imperative that we understand this dynamic so that the proper regulations and planning can be implemented.

During disasters it is expected to have a large number of injured/sick people requiring medical aid at the same time; the response scenario is of the greatest importance. The ambulance usage can be improved by a smart routing (Talarico et al., 2014). Nowadays, digital maps are increasingly common to greatly improve the optimization of evacuations performed by emergency vehicles such as ambulances or fire trucks. With the progress that has been made in technology, these maps are becoming more sophisticated, in the way that they are able to find specific locations, draw routes and so forth. The objective of this part of the work is to develop a system to help create routes based on the emergencies given in El Paso, Texas using a system of neighborhoods of ants that allows them to create routes to take care of patients affected by a dust event or other types of emergencies in a quick way. The bio-inspired algorithms are a technique of artificial intelligence
focused on the solution of different problems, especially optimization problems (Kolavali & Bhatnagar, 2009).

Methodology and Aims

To fill these gaps in the literature,

- I analyze the health associations of dust events in El Paso County, Texas, an area with Köppen climate classification type BW [arid; Chihuahuan Desert of Texas (CDT)] using data from the Texas Hospital Inpatient Research Data files (RDF) at the Texas Department of State Health Services (TDSHS) from 2010-2014. This set of data classifies hospital admissions based on the Principal Diagnostic Code.

- I develop a bio-inspired algorithm system to help create ambulance routes based on the emergencies given in El Paso, Texas using a system of neighborhoods of ants that allows them to create routes to take care of patients affected by a dust event or other types of emergencies in a quick way.

- I study the association (day of and 7 days after) in El Paso, Texas, between elevated exposure of 100μg/m³ increments in daily maximum of hourly PM₁₀ and/or 10mph daily maximum wind speed increase (day of and 7 days after), representing dust exposure, and hospital admissions due to neurodegenerative disease (ND; Parkinson’s, Alzheimer’s, and Huntington’s), mental illness (MI -depression and anxiety), Valley Fever (VF), Asthma, Coronary Atherosclerosis, other associated diseases which is the aggregated effect of the most frequent hospitalizations associated with at least 5% of hospitalizations and independently (AD; Respiratory Diseases, Circulatory System Diseases, Digestive Diseases, Genitourinary Diseases, Births, Encounter for antineoplastic Chemotherapy, Unspecified Septicemia, Other Chest Pain, Dehydration, Cellulitis and Abscess of Leg,
Osteoarthritis, Diabetes Mellitus And Mental Disorders) and all ICD-9 categories by
hospital admissions by Codes from the International Classification of Diseases, Ninth
Revision (ICD-9) category and assess the mediating or moderating role of demographic
factors (age, and SES -income, and educational attainment).

This research project is conducted by exploring the following three specific aims:

**Specific Aim 1.** Characterization of a preliminary predictive model to analyze the effects
of dust events in a society with Köppen climate classification type BW and its long-term health
effects.

Hypothesis: It is hypothesized that the proposed predictive model will be able to analyze
involving factors related to hospitalization during DEs in a society with Köppen climate
classification type BW in order to predict future hospitalization rates based on dust events. Several
hospitalizations will increase due to DE.

**Specific Aim 2.** Creation of an efficient route of ambulances using an intelligent tool for
decision making, via a bio-inspired algorithm at El Paso County during DEs from 2010-2014.

Hypothesis: It is hypothesized that the proposed algorithm will provide time effective
routes during the expected high demand of ambulances on a DE day.

**Specific Aim 3.** Determine via a Poisson regression modeling if increasing increments of
PM$_{10}$ and/or wind speed during DEs is associated with an increase in hospital admissions due to
acute or accelerated disease progression of ND, MI, VF, Asthma, Coronary Atherosclerosis, AD
(independently and in aggregation), and all ICD-9 categories and determine the mediating/moderating role of the demographic factors, in the County of El Paso, TX.

Hypothesis: It is hypothesized that the exposure to elevated PM$_{10}$ and/or wind speed during DEs will be positively associated with hospital admissions due to ND, MI, VF, Asthma, Coronary Atherosclerosis, AD and all ICD-9 categories at different lag days, being the highest effect during the actual day of DE. SES will moderate the association with some hospital admissions due to elevated PM and/or Wind speed exposure during DE, with admissions being higher among individuals living in areas of lower SES. In addition, age will mediate the association between overall hospital admissions and air pollution exposure during DE.

**Significance**

My study is notable for both having been planned to include inpatient hospitalization and also being a more comprehensive study in that it investigates the associations of ambient particulate matter and maximum wind speed during DE due to acute or accelerated disease progression of ND, MI, VF, Asthma, Coronary Atherosclerosis, AD, and all-ICD-9-category diagnosis and the mediating/moderating role of age, gender, and health disparities by the SES in the desertic region of CDT. In addition, identifying the algorithm necessary to optimize the ambulance routes during the high demand in DEs at El Paso County. Few studies have been explicitly conducted to analyze the critical relationship between air quality and human health in the regions of CDT. This study’s results will help to reduce not only the risks of the associated diagnosis but also mortality, morbidity, medical costs, health disparities and social and economic inequalities.

Therefore, it is important to study DEs health associations, because these events are expected to rise globally due to climate changes and the rise in desertification caused by natural and anthropogenic events. This could lead to a substantial increase in transport of foreign, invasive,
and potentially new pathogenic microorganisms that could alter equilibrium balance in downwind ecosystems, remodel virgin environments, and/or affect human and ecosystem health (Behzad et al., 2018).
References


Chapter 2: Characterization of a Preliminary Predictive Model to Analyze the Effects of Dust-Storms Events in a Society with Köppen Climate Classification Type BW and its Long-Term Health Effects.
Conceptualization of a Predictive Model for Analysis of the Health Outcomes of Dust Events in a Society with Köppen Climate Classification BW

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Abstract. High concentrations of particulate matter (PM) in the air during Dust Events (DEs) are silently impacting the health of people without their awareness. It has been demonstrated that exposure to increased levels of PM can increase the susceptibility to respiratory, circulatory, mental and other diseases due to inflammation. In addition, living in a city with Köppen climate classification type BW (arid) and subsequently with frequent high levels of PM could have a negative impact on the population’s health. There are very few studies available in the southwestern United States pertaining to the associations between exposure to atmospheric aerosol after DEs and hospitalizations. Therefore, we will do a conceptualization of a predictive model to analyze the health effects of DEs in a society with Köppen climate classification type BW. We will do a representation of a system in order to understand how the DEs, hospital admissions, elevated PM levels, socioeconomic status (SES), and demographic factors work together. Preliminary results indicate that there are more admissions in all primary diagnoses during a DE than in a regular day.

Keywords: ecological data mining, multivariable analysis, pattern recognition, structural equation, long term health effects, oxidative stress, inflammatory responses, social economic data.

1 Introduction

The Southwestern region has been identified as one of the most persistent dust producing regions of North America (Orgill and Schmidel, 1976; Prospero et al., 2002). Exposure to inhalable particulate matter of 10 micrometers or less in diameter (PM10) originating from desertic landscape during DEs can reach toxic levels (Song et al., 2007). El Paso’s ambient air has reached hazardous levels of PM10 above 4000 μg/m³ with near zero visibility due to these natural events (Rivera et al., 2010), thus exceeding the primary and secondary 24-hour standard of 150 μg/m³. According to the National Ambient Air Quality Standards (NAAQS), this standard should not be exceeded more than once per year based on an average of 3 years (EPA, 2018). In El Paso, TX, DEs occur on average 14.5 times per year (Novlan, D., Hardiman, M., & Gill, T., 2007),
Conceptualization of a Predictive Model for Analysis of the Health Outcomes of Dust Events in a Society with Köppen Climate Classification BW

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Abstract. High concentrations of particulate matter (PM) in the air during Dust Events (DEs) are silently impacting the health of people without their awareness. It has been demonstrated that exposure to increased levels of PM can increase the susceptibility to respiratory, circulatory, mental and other diseases due to inflammation. In addition, living in a city with Köppen climate classification type BW (arid) and subsequently with frequent high levels of PM could have a negative impact on the population’s health. There are very few studies available in the southwestern United States pertaining to the associations between exposure to atmospheric aerosol after DEs and hospitalizations. Therefore, we will do a conceptualization of a predictive model to analyze the health effects of DEs in a society with Köppen climate classification type BW. We will do a representation of a system in order to understand how the DEs, hospital admissions, elevated PM levels, socioeconomic status (SES), and demographic factors work together. Preliminary results indicate that there are more admissions in all primary diagnoses during a DE than in a regular day.

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Introduction

The Southwestern region has been identified as one of the most persistent dust producing regions of North America (Orgill and Sehmel, 1976; Prospero et al., 2002). Exposure to inhalable particulate matter of 10 micrometers or less in diameter (PM$_{10}$) originating from desertic landscape during DEs can reach toxic levels (Song et al, 2007). El Paso’s ambient air has reached hazardous levels of PM$_{10}$ above 4000 μg/m$^3$ with near zero visibility due to these natural events (Rivera et al., 2010), thus exceeding the primary and secondary 24-hour standard of 150 μg/m$^3$. According to the National Ambient Air Quality Standards (NAAQS), this standard should not be exceeded more than once per year based on an average of 3 years (EPA, 2018). In El Paso, TX, DEs occur on average 14.5 times per year (Novlan, D., Hardiman, M., & Gill, T., 2007), which are conditions that resemble those of the Dust Bowl during the 1930’s at the Southern Plains of Texas (Lee and Gill, 2015). Deadly respiratory health problems were prevalent during that period (Alexander, Nugent and Nugent, 2018).

Recent literature has shown that exposure to desert-related particles during DEs is associated with increased hospitalizations due to respiratory or circulatory-related problems (Zhang et al. 2016). However, not much is known about the possible effects of exposure to desert-related particles during DEs on mental and neurological-related health problems. Because it has been shown that inhaled particles induce an inflammatory response that starts in the lung, spills into the circulatory system, and ultimately can reach the brain, I suspect that exposure to very high levels of particles from natural sources during DEs might increase hospitalizations due to mental and neurological-related health problems. Understanding the impact of environmental exposures on these types of health problems is important as depression, Parkinson’s disease and Alzheimer’s disease are the three most prevalent and costly mental and neurodegenerative diseases in the U.S.
(Weintraub, Karlawish & Siderowf, 2007). Furthermore, socially disadvantaged individuals, such as those of low socio-economic status (SES) or those who are frequently exposed to discrimination and isolation (e.g., racial and ethnic minorities) tend to be more susceptible to the health effects of air pollution exposure (Grineski et al., 2015; Halonen et al., 2016). In addition, evidence suggests that factors such as age, gender, and ethnicity might affect the association between exposure to particles and health problems, but this mediating role is not clear (Howard, Peace & Howard, 2014).

During DEs -particularly in arid regions- particles from deserted landscapes get lifted into ambient air by high wind speeds where they combine with particles emitted by urban sources (e.g., vehicles, industry source components that are in the air or settled on the roads) as well as with biological particles in nature (e.g., spores, fungi) (Fuzzi et al., 2015). Currently, there is little understanding of the health effects induced by exposure to the above-mentioned particle mixtures, which during DEs can reach high, unsafe concentrations. Exposure to DEs is more frequently experienced by populations that live in arid and semiarid regions of the world. In the United States, DEs are frequent within and around the Chihuahua Desert of Texas, which is where the proposed study will focus on. Addressing the associations between DEs and hospitalizations in these arid regions of the US will greatly inform the scientific community, habitants, and the environmental and social authorities who are responsible for implementing the proper adjustments. The following sections will provide a review of the relevant literature to and identify gaps that illustrate the significance of the proposed study.
Literature Review

Description of the Chihuahuan Desert (El Paso)

This study will focus on parts of the Chihuahuan Desert (Texas) which is the most persistent dust producing regions of North America (Lee et al., 2009; Novlan et al. 2007; Rivera et al. 2009 and 2010) (see Figure 2.1). The high frequency of dust storms in these regions are due to large-scale dry climate (climate type -according to the Köppen climate classification system- cold desert (BWk), hot desert (BWh) (Lee et al., 2012; Lee and Tchakerian, 1995; Rivera et al., 2009; Bernier et al., 1998; Li et al. 2018).

The Chihuahuan Desert is the one of the most significant sources of dust in the Western Hemisphere (Prospero et al., 2002). In this region, agricultural lands, ephemeral lakes, and dry river beds have been identified as the main sources of the dust from this desert that is blown into El Paso, Texas (Lee et al., 2009). Within the Chihuahuan Desert, I will focus specifically in dust events occurring in El Paso, Texas, which is the largest city in the US that is located in the central part of the Chihuahuan Desert (see Figure 2.1). In El Paso, dust events have been identified as important environmental hazardous events. Based on data collected at the El Paso International Airport from 1932 through 2005, dust events in El Paso occur on average 15 times a year and last an average of 2 hours each (Novlan et al., 2007). In this region, dust storms occur most commonly during the months of December through May when ambient air is dry and winds can reach high speeds (>25 mph), blowing primarily on strong westerly and southwesterly winds (Novlan et al., 2007). At wind speeds greater than 25 mph, dust can be raised into the atmosphere and/or transported for long distances by synoptic-scale weather systems (horizontal length scale of the order of 1000 kilometers or more), which results in widespread exposure to ambient air particle mixtures (Lee et al., 2009).
Air Pollution

Particles, also called atmospheric aerosols, that are less than 10 µm in diameter (PM$_{10}$) have very low sedimentation speeds under gravity and may remain in the air for days before eventually being washed out by rain or impacted out onto vegetation or buildings, but they can be re-suspended from surfaces during a DE. These particles are a regulated environmental pollutant, being responsible for reducing visual range, soiling surfaces, and negatively impacting human health (Colls, 2002). PM$_{10}$ concentrations can reach very high levels during DE, particularly in desert environments or near agricultural fields or unpaved roads where high wind speeds can lift surface particles (Jacob, et al., 2009). Ambient levels of PM$_{10}$ in the US are regulated by the US Environmental Protection Agency (US EPA). Standards for PM$_{10}$ consist of 150 µg/m$^3$ during 24-hour periods and are not to be exceeded more than once per year on average over 3 years (visit https://www.epa.gov/criteria-air-pollutants/naaqs-table). Peak hourly concentration of PM$_{10}$ in El Paso during a DE has reached 1,955.2 µg/m$^3$.

Aerosol content in the atmosphere depends on its origin (urban, rural, marine, desertic or combined), as well as physical properties and chemical composition, all of which induces different health effects within each environment (Carvalho-Oliveira, 2015). Aerosols may have either a primary or secondary origin, be solid or liquid, and come from biological or inorganic sources. Primary sources of particles include industrial processes, transport-related processes, unpaved roads, fields, fires, wood combustion, marine aerosol, and mineral dust aerosol (MDA- principal component from all the atmospheric aerosol in the planet) (Fuzzi et al., 2015). Secondary particles result from complicated reactions of chemicals in the atmosphere from compounds such as sulfur dioxides and nitrogen oxides which are typically emitted from power plants, industrial processes, and automobiles (EPA, 2018b).
Globally, it is estimated that the main sources of particulate matter contributing to urban air pollution are: 25% by traffic, 15% by industrial activities, 20% by domestic fuel burning, 22% from unspecified sources of human origin, and 18% from natural dust and salt (Karagulian et al., 2015). However, in a dusty arid region such as in El Paso, these percentages are likely very different. At El Paso, 35% of the total mass concentrations in the PM\textsubscript{10} fraction accounted for Major elements from geologic sources, indicating that geologic sources in the area are the dominant PM sources through the year (Li et al., 2001).

**Characterization of Dust Storms**

Within the Southwestern US, DEs are caused by synoptic-scale Pacific cold fronts moving across the desert from west to east, and cyclones developing and intensifying to the northeast (Rivas et al., 2014). All these factors create the conditions for DEs, which is defined as an event with PM\textsubscript{10} above 150 μg/m\textsuperscript{3} while wind speeds above 10 m/h (see Figure 2.1) (Hosiokangas et al., 2004; Lee et al., 2009; Rivera et al., 2009). Low wind conditions can also lead to elevated levels of pollutants and particulates in the air. Nevertheless, per a study conducted in El Paso (Grineski et al., 2011) and one in Lubbock (Lee and Tchakerian, 1995), low wind conditions are not or rarely associated with dust events.
Figure 2.1 Definition of a Dust Event for this study; Wind speed above 10 m/h and PM$_{10}$ above 150 µg/m$^3$.

Desert dust can be transported across the world by arid and semi-arid regions where loose soil can easily be lifted during high wind speeds (Lim & Chun, 2006). For instance, dust from the Sahara Desert can be transported across the Atlantic Ocean and reach northeastern South America, the Caribbean, Central America, and southeastern United States (Kanatani et al., 2010). This transportation to distant regions by DEs is generated when strong surface winds lift up fine grained dust particles into the air and strong turbulence or convection diffuses the dust, particulate material, biological aerosols and pollutants (Shao, 2008; Zhang et al., 2016). It is estimated that 75% of the global dust emissions is due to natural origin, while 25% are related to anthropogenic (primarily agricultural) emissions (Ginoux et al., 2012), with the Sahara Desert as the largest source of natural mineral dust aerosol (Karanasiou et al., 2012).

It is estimated that the total dust deposition rate during a DE at El Paso, TX is approximately 195.5 g/m$^2$/yr, where values are elevated in comparison to dust deposition elsewhere in the region, and closer to other global desert areas (Rivas et al., 2014). The principal size class of deposited sediment during DEs is sand (86.81%) followed by 9.25% of PM$_{10}$ and 3.94% of PM$_{2.5}$. An air monitoring station near the study area at the same times indicated peak hourly PM$_{10}$ values of 1955.2 µg/m$^3$ and for PM$_{2.5}$ 288.33 µg/m$^3$ (Rivas et al., 2014).
The mineralogy of DE particles at El Paso, TX is dominated by quartz (silicon dioxide) with the presence of other common minerals such as plagioclase, gypsum, and calcite (Rivas et al., 2014). In addition to the inorganic particulate matter contained in the dust during a DE (contained in the PM), there are substantial quantities of foreign microorganisms derived from the downwind atmosphere, terrestrial, and aquatic environments (Zhang, Zhao & Tong, 2016). Significant increases in the concentration of bacteria and fungi are commonly detected in dust clouds during sandstorm events (Tang et al. 2018). DE are known as one of the most far-reaching vehicles for transport of highly stress resistant and potentially invasive/pathogenic microorganisms across the globe (Weil et al. 2017).

Dust, Fugitive Dust, Aerosols and their Health Effects

In the Southern High Plains, the dominant aerosol elemental content during DE includes Al, Si, S, Cl, K, Ca, Ti, Mn, Fe, and Zn, with minor and trace elements (Cr, Ni, Cu, Rb, Zr, and Pb) (Gill, Stout and Peinado, 2009). On the other hand, Garcia et al. (2004) found that the elements in El Paso’s dust-emitting soil are largely the same elements found in the Southern High Plains (Al, Ca, K, Zn, Cr, Ni, Cu, Pb and Mn), plus Na, Ag, As, Cd, Mo, Sb, Ba, Co, and Be (Li et al., 2001), which are fugitive dust sources that might increase during dust events. A recent study near Las Vegas, NV during a DE showed that accumulated particles on the road are re-suspended. These suspended particles are composed of a more complex mixture of elements, including Al, V, Cr, Mn, Fe, Co, Cu, Zn, As, Sr, Cs, Pb, U, and others (Keil et al., 2016). This fugitive dust are disease precursor with hazardous effects on human health (e.g. carcinogenic and non-carcinogenic) (Khan, & Strand, 2018; Kioumourtzoglou et al., 2015). Furthermore, Huang et al. (2014) found house air-
conditioner dust to be more hazardous than road dust; within these particles lead was the most abundant element, followed by arsenic.

Several studies have hinted that exposure to particle air pollution during dust events could have a direct impact on human health (Anderson et al., 2013). This is because the PM<10 μm can penetrate into the lungs and exposures are based upon respirable dust (≤5 μm) (Bhagia, 2012; Middleton, 2017). For example, the size fractions of silica in ambient dust is in the range of 2.5-15 μm and PM<2.5 μm can penetrate into deep lung tissue (Bhagia, 2012). Besides the composition of particles, and the size and surface area of breathable particles, air pollution has been found to affect the degree of oxidative stress and the release of cytokines, accelerating inflammation in the body (Dostert et al., 2008; Ghio et al., 2004) (see Figure 2.2). Systemic inflammation, endothelial activation, and low-grade inflammation caused by inhaled traffic-related PM (Li et al., 2015; Chiarelli et al., 2011), has been hypothesized as a key factor in the pathway leading to detrimental structural and cognitive effects, as well as neurodegenerative and mental illnesses (Calderón-Garcidueñas et al., 2015; Heusinkveld et al., 2016).

![Figure 2.2 Silica activate IL-1B secretion in human macrophages. Analyzed in media supernatants (SN) and in cell extracts (Cell). From Dostert et al. 2008](image)

In addition, recent studies have shown that particle air pollution during DE increase hospitalizations for expected causes such as respiratory and cardiovascular disorders (Khaniabadi...
et al., 2017; Yu, Chien, and Yang, 2012). Even more, recent studies suggest that silica dust influence brain function and aggravates spinal cord injury. Exposure to silica dust increases epithelial permeability in patients with silicosis who smoke (Nery et al., 1993). Keil et al. (2018) performed an exposure study to dust at the southwest USA with a PM median diameter of 4.6, 3.1, and 4.4 μm. Results showed an overall reduction in the immune response rather than a direct effect of dust samples on neuronal protein-specific antibody production, but neurotoxicity cannot be ruled out as a concern. Also, increased levels of serum creatinine -a marker for kidney function- were found. A previous study (Keil et al., 2016 b) showed that brain CD3+ T cells were decreased in number after dust exposure with silica and heavy metals present in the southwest soil.

Hospitalizations after a DE have been reported to have a prolonged effect on the day of the DE and on the week after the DE (Yu, Chien & Yang et al., 2012). Therefore, in this study, hospitalizations will be under particular scrutiny during those day(s) when a dust storm event is taking place, as well as all throughout the following week.

**Biological Aerosol Particles and its Health Effects**

Sandstorms from the Sahara Deserts transmit roughly a billion tons of dust across the atmosphere, and the region is considered one of the major sources of the intercontinental dust transport (Griffin 2007). The Gobi and Taklamakan Deserts in Asia are the second largest sources (Zhang et al., 2016). These dust plumes can reach as far as the Americas (Husar et al., 2001), transporting trillions upon trillions of microbes into the air and downwind destinations along their intermediate path which are added to the own desert microbiome (Behzad, Mineta & Golobori, 2018). By some estimate, a cubic meter of air contains hundreds of thousands of microorganisms (Prussin et al., 2015; Brodie et al., 2007), with an extensive diversity of taxa (Franzetti et al., 2011).
Mineral dust aerosol (MDA) contains primary biological aerosol particles (PBAPs) and has a large range of different biological components, including microorganisms (bacteria, archaea, algae and fungi) and dispersal material (pollen, fungal spores, viruses and biological fragments) (Fuzzi et al., 2015). Furthermore, large deserts create their own Dust Storm Derived Microbiota (DSM) (Griffin, 2007). This microbiota includes highly stress-resistant microorganisms (bacteria and fungi) that are capable of thriving in harsh environmental conditions with restricted water and nutrient availability, extreme temperatures, and UV irradiation (Chan et al. 2013; Etemadifar et al., 2016). Viruses on the other hand can undergo degradation by atmospheric processes and can experience a possible loss of their toxic effects in the source regions as they are carried away (Despres et al., 2012). This large-scale transmission of highly resistant microbial contaminants raises concerns with regards to human health (Chung and Sobsey, 1993 and Cox, 1995).

It has been proven that viruses present during DE are taxonomically diverse (Zablocki et al., 2016) and are transported by the dust across long distances (Yu et al., 2012; Chung and Sobsey, 1993). This movement leads to significantly higher cases of Influenza A virus, typhus, cholera, malaria, dengue and West Nile virus infection than is typically observed during normal non-DE days (Griffin, 2007). Examples of influenza outbreaks type A virus and H5N1 avian influenza occurred in Taiwan, Japan and South Korea during the Asian Dust Storms (ADS) that originated in the deserts of Mongolia and China (Chen et al. 2010).

Bacterial epidemics are strongly linked to DEs. Bacterial meningitis is associated with DEs, which is a major predictor of the timing of meningitis epidemics (Agier et al., 2013). In 1935, Kansas experienced a severe measles epidemic during the Dust Bowl. Hospital admissions were largely for acute respiratory infections such as pneumonia, sinusitis, laryngitis and bronchitis (Brown et al., 1935). Similar cases of respiratory infections due to DE can be found in Western
China (Ma et al., 2017). The epidemics of pulmonary tuberculosis was similarly linked to ADS in China (Wang et al., 2016). ADS were also positively associated with diabetes in women (Chan et al., 2018).

Another infectious disease presumably caused by fungi during a DE is the Valley Fever, whose fungal causative agents (Coccidioides immitis and Coccidioides posadasii) are primarily found in hot and arid desert soil (Kirkland and Fierer, 1996). The outbreaks of Kawasaki disease (a serious heart complication acquired in childhood) was linked to a fungal Candida species found in DE from China (Rodo et al. 2014; Tong et al. 2017).

**Inflammatory Response Pathway**

The inflammatory response helps the body fight and clear infection, remove damaging chemicals, and repair damaged tissue. However, frustrated phagocytosis (an action where a phagocyte fails to engulf its target and toxic agents can be released) can have a harmful effect on the body (Dostert et al., 2008). At its worst, inflammation can provoke cancer (Tili et al., 2011). There are two pathways that link PM air pollution (gases, ultrafine particles, and nanoparticles present in the particulate matter like silica from the dust) to adverse health outcomes (Shrey et al., 2011).

The first is a direct pathway, which consists of the local oxidative stress/inflammation effects of pollutants on the cardiovascular system, blood, and lung receptors (Garcia et al., 2015). This direct pathway involves the direct translocation (the dominant method of trapping and processing particles in the lung tissue) of inhaled fine particles present in the PM into the circulatory system causing intracellular oxidative stress releasing cytokines and chemokines (Nemmar et al., 2010). Particles can readily cross the pulmonary epithelium or the lung–blood barrier due to their particle size, charge, chemical composition, and propensity to form aggregates (Oberdörster et al., 2004).
Once such particles like silica are in circulation, they lead to further deleterious effects such as local oxidative stress and inflammation (Brook et al., 2010). The mechanism starts with local inflammation in the upper and lower respiratory tract resulting in increased levels of pro-inflammatory mediators (e.g., IL-6, IL-8, and of tumor necrosis factor alpha (TNF-α) following into the circulatory system inducing low-grade peripheral inflammation (see Figure 2.3) (Olvera et al., 2018). An example of this direct pathway is that in rats, a three-hour PM2.5 exposure has been shown to lead to a rapid increase of reactive oxygen species (ROS) generation in the heart and lungs (Gurgueira et al., 2002; Li et al., 2015).

Figure 2. 3 Systemic inflammation mechanism due to DE. Asbestos crystals or silica are too large to be phagocyted by macrophages and so are subject to “frustrated” phagocytosis. This leads to activation of NADPH oxidase and the generation of reactive oxygen species. This event activates the Nalp3 and ASC inflammasome promoting the processing and release of the potent proinflammatory molecule interleukin-1β. From O’Neill et al., 2008.

The second pathway is the classical pathway, which explains the indirect effects mediated through pulmonary oxidative stress and inflammatory responses (Nemmar et al., 2003; Tonne et al., 2016). It begins when inhaled traffic-related PM enters the body through the airway to the lungs and causes a local inflammatory response at the bronchial epithelial cells and from alveolar
macrophages (Bai and Sun, 2015). Bronchial epithelial cells and alveolar macrophages are in prolonged contact with the inhaled particulates when clearing them from the lung, which can initiate and sustain inflammatory responses (Dostert et al., 2008). Silica are sensed by the Nalp3 inflammasome, whose subsequent activation leads to interleukin-1β secretion. The onset of this inflammatory response, at a cellular level, is triggered by the release of TNF-α and IL-1β which regulate the expression of various secondary cytokines and chemokines, including IL-6 and IL-8 (Schwarze et al., 2013; Mormon and Plumlee, 2013).

**Health Disparities**

Health disparities are health differences that adversely affect socially disadvantaged groups (Krieger, 2016). Health disparities are systematic, reasonably avoidable health differences according to race/ethnicity, skin color, religion, or nationality; socioeconomic resources or position (reflected by, e.g., income, wealth, education level, or occupation); gender, sexual orientation, gender identity; age, geography, disability, illness, political or other affiliation; or other characteristics associated with discrimination or marginalization. These categories reflect social advantages or disadvantages when they determine an individual’s or group’s position in a social hierarchy (Braveman et al., 2011). Furthermore, inequities in social determinants of health, including neighborhood poverty, crime rates, and reduced access to high-earning jobs, housing, transportation, and healthy foods significantly contribute to these disparities (Cooper et al., 2016). Disparities in health and its determinants are the metric for assessing health equity (Gee, Walsemann, & Brondolo, 2012). An example of health disparities is that being overweight is negatively associated with income, education level, and occupation at the municipality level (Kinge et al., 2016).
Moreover, social factors (e.g., stress, health disparities, low access to resources) may induce intrinsic vulnerability to the effects of air pollution, including a pro-inflammatory phenotype that results in increased inflammatory reactivity to air pollution exposure that may be heritable (Wu et al., 2016; Heusinkveld et al., 2016). An example of this is the impact of PM2.5 on markers of systemic inflammation and oxidation in those with multiple pre-existing cardiovascular diseases with elements of metabolic syndrome (e.g. obesity, diabetes, hypertension and smokers) (Aguilar et al., 2015).

Opposite to health disparities, gender, age and genetics are a natural disorder cause. For example, a study by Reynolds et al. (2016) found that women experienced a significantly greater decrease in incidence of myocardial infarctions compared with men. Other investigators suggest that cumulative stress may result in affecting biological processes, such as shortening telomere length. The length of telomeres on chromosomes declines with age and may be an indicator of remaining life expectancy. Some evidence suggests that there is a systematic relationship between educational attainment and the length of telomeres (Adler et al., 2013; Kaplan, 2014).

**Dust Storm Projections**

For the last 50 years, an acceleration of changes on the average climate conditions (IPCC, 2007a) has been observed. The average global temperature has increased by 0.7 °C and it is expected to increase between 1.8 and 4.0 °C by the year 2100 (IPCC, 2007b; Hansen et al., 2006). The frequency of dust storms has increased during the last decade and forecasts suggest that this will continue to rise in response to anthropogenic activities and climate change (Schweitzer et al., 2018). El Paso del Norte is the region that has the highest probability for DE (Rivera, Rivera et al., 2009).
Climate change poses unprecedented threats to human by impacts on health, food and water security, heat waves and droughts, dust storms, and infectious diseases; whether or not humanity will successfully adapt is not yet known (Barrett et al., 2015). Some infectious diseases and their animal vectors are influenced by climate changes, resulting in higher risk of typhus, cholera, malaria, dengue and West Nile virus infection which are carried by DE (Franchini & Mannucci, 2015). Moreover, climate drivers (increase of temperatures, changes in precipitations patterns, extreme weather effects), environmental changes (changes in pollutant exposure, changes in allergens production, timing and distribution), urban landscapes, emission patterns, and social and behavioral context (income, education, sensitivity, adaptive capacity and housing quality) can affect an individual’s or a community’s health vulnerability over the time (Global Change, 2017).

Methodology

Data Sources

Hospital admissions: Five years of data were obtained from the Texas Hospital Inpatient Research Data files (RDF) from the Texas Department of State Health Services (TDSHS) for years 2010 through 2014 for El Paso TX. The data included the following five variables: the date of admission, census block group of the patient, the patient’s age, gender, ethnicity, and the principal diagnostic code from the International Classification of Diseases, Ninth Revision (ICD)-9 (see Table 2.1). The principal diagnostic code was preferred over other diagnostic codes because it better captures the exacerbations of disease as opposed to other diagnostics due to existing diseases (CMS, 1990).

PM and wind speed data: Hourly averages of PM$_{10}$ concentrations, wind speed (m/h), relative humidity (%), and mean, minimum, and maximum temperature ($^\circ$ F) measured at Continuous Air Monitoring Stations (CAMS) located in El Paso, Lubbock, Midland and Amarillo, listed in Table 1, from 2010-2014 will be downloaded from the Texas Commission on Environmental Quality
(TCEQ) website. PM$_{10}$ and wind speed missing data will be interpolated using a temporal linear method in cases where the data were missing for three consecutive hours or less; days with data missing for four or more consecutive hours will be excluded from the analysis. It is expected that of the total dataset, about 1% of all analyzed days would require missing data interpolation; after interpolation, the dataset will be over 99.7% complete.

**Socio-economic data:** Economic characteristics, including income, level median income, poverty, occupation and education for each patient address census block group will be obtained from the U.S. Census Bureau's American Community Survey for the 2010-2014 period. It will help us to identify susceptible individuals. This information will be connected with the RDF’s Address Census Block Group code of each hospitalized patient in the CDT and HPWT.

**Demographic data:** Population increase or decrease (in millions) data between 2010-2014 will be obtained from the census data of statistics in the county of El Paso, Texas, to remove these non-environmental confounding elements (population increase or decrease).
Table 2. Codes from the International Classification of Diseases, Ninth Revision (ICD)-9.

<table>
<thead>
<tr>
<th>Code Range</th>
<th>Diagnosis</th>
<th>Code Range</th>
<th>Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 001-139</td>
<td>Infectious and parasitic diseases</td>
<td>10 580-629</td>
<td>Diseases of the genitourinary system</td>
</tr>
<tr>
<td>2 140-239</td>
<td>Neoplasms</td>
<td>11 630-679</td>
<td>Complications of pregnancy, childbirth, and the puerperium</td>
</tr>
<tr>
<td>3 240-279</td>
<td>Endocrine, nutritional and metabolic diseases, and immunity disorders</td>
<td>12 680-709</td>
<td>Diseases of the skin and subcutaneous tissue</td>
</tr>
<tr>
<td>4 280-289</td>
<td>Diseases of the blood and blood-forming organs</td>
<td>13 710-739</td>
<td>Diseases of the musculoskeletal system and connective tissue</td>
</tr>
<tr>
<td>5 290-319</td>
<td>Mental disorders</td>
<td>14 740-759</td>
<td>Congenital anomalies</td>
</tr>
<tr>
<td>6 320-389</td>
<td>Diseases of the nervous system and sense organs</td>
<td>15 760-779</td>
<td>Certain conditions originating in the perinatal period</td>
</tr>
<tr>
<td>7 390-459</td>
<td>Diseases of the circulatory system</td>
<td>16 780-799</td>
<td>Symptoms, signs, and ill-defined conditions</td>
</tr>
<tr>
<td>8 460-519</td>
<td>Diseases of the respiratory system</td>
<td>17 800-999</td>
<td>Injury and poisoning</td>
</tr>
<tr>
<td>9 520-579</td>
<td>Diseases of the digestive system</td>
<td>18 E000-E999</td>
<td>Supplementary classification of external causes of injury and poisoning</td>
</tr>
</tbody>
</table>

Model Analyses

Dust storm periods will be identified by matching the hourly average PM$_{10}$ exceeding 150 μg/m$^3$ and high winds above 10 m/h (Rivera et al., 2009). In order to estimate the influence of dust storm’s particulate matter from hospitalizations, a regression model will be generated to determine the correlations between the identified dust storms and hospitalizations during one-week period (the day of the storm and week after the dust storm) identified in the county of El Paso.

SES data from the U.S. Census Bureau's American Community Survey for the 2010-2014 period will be connected with the RDF’s Address Census Block Group code of each hospitalized patient identified. An association between diseases outcomes and SES, (including income, poverty level, occupation and education level at county level in El Paso, TX) will be looked upon. Also, it will be searched if there is a remarkable reduction/increase in the incidence of hospitalized
residents with any disease that is affected by dust events from 2010-2014. A search will be conducted for an association between diseases and SES, including age, sex, and race at county level county level in El Paso, TX.

Model analysis will be applied using data mining. A conceptual model will be applied to establish a basic model to explore the associations between the predictor variable (Dust events) and response variables (admissions, age, sex and SES). I will remove long-term trends and seasonal patterns from the data to protect against confounding by omitted variables. I will control for season and long-term trend with a natural cubic regression spline with 1.5 degrees of freedom (df) for each season and year (corresponding to 6 df per year). In addition, I will include natural splines with three df for temperature on the day of the admission and with 2 df for the six following days and a linear term for daily average humidity and dummy variables for the day of the week effect and public holidays. Once the data is normalized, each diagnosis code will be categorized into; acute, chronic and mental, in order to have a better understanding of the associations between DEs and diagnosis. Separated models will be run for each outcome of significant primary diagnosis. Models for present (2010-2014) and future projections (2020 and 2050) will be modeled separately.

In addition, geographic maps will be created in each municipality indicating their PM$_{10}$ levels and hospital admissions percentage during a DE and their association between each socio-economic factor per 1000 population in El Paso, TX between 2010 and 2014 and projected outcomes (2020 and 2050). This will be done by using the Empirical Bayesian Kriging (EBK) Regression Prediction Method by ArcGIS (ESRI, Redlands, CA, USA).
Preliminary Results

We propose that projected health outcomes due to DEs are manifested by patient hospitalization which is associated with environment, demographic and socio-economic factors as the following model and formulas indicate (Figure 2.4).

\[ \alpha = i (\gamma + \delta + \epsilon + \iota) \pm id, \quad (1) \]

Where Educational attainment (\( \alpha \)) is defined by: \( \gamma \)= Neighborhood, \( \delta \)= Access to education, \( \epsilon \)= Parent expectations about children, \( \iota \)= Local inequities/disparities (these factors are rated from 1 to 10, being 1 the lowest given value and 10 the highest according the present and projected ratings for 2020 and 2050 in each Census Block Group code at the El Paso County) and \( \iota \)= Income (value given from the Census Block Group code at the El Paso County and projected values for 2020 and 2050).

\[ Z = (\zeta)^{gi} \quad (2) \]

Where Occupation (\( Z \)) is defined by: \( \zeta \)= Occupation (value given from the Census Block Group code at the El Paso County) and \( gi \)= Inequities/disparities based on globalization (rated from 0 to 10, being 1 the lowest given value and 10 the highest according the present and projected ratings in each Census Block Group code at the El Paso County).
Conceptualization of a Predictive Model for Analysis of the Health Outcomes of Dust Events.

Figure 2.4 Conceptual predictive model of DEs and its health outcomes in a society of BW climate.

\[ \Theta = \sum (\kappa, \lambda, \mu, \xi, o) \]

\[ i = 1 \]
Where Neighborhood poverty ($\theta$) is defined by: $\kappa$= crime rates, $\lambda$ = stress provoked by discrimination, $\mu$= health disparities, $\xi$= Neighborhood with a certain level of pollution according to the type of industry and $\sigma$= access to medical service and information.

$$\Phi = \eta \{ \alpha + (Z + \Theta) \}, \quad (4)$$

Where SES ($\Phi$) is defined by: $\eta$= income, $\alpha$ = Educational attainment, Z= Occupation, $\theta$= Neighborhood poverty.

$$X = \sum_{i=1}^{n} (\xi, \tau, \sigma), \quad (5)$$

Where Demographic Factors ($\chi$) is defined by: $\zeta$= Ethnicity, $\tau$= Age and $\sigma$= Sex.

$$\dot{\omega} = \omega (\dot{\omega} + (\Psi \delta + \gamma) + \dot{u}), \quad (6)$$

Where Desertic factors ($\dot{\omega}$) is defined by: $\dot{\omega}$= Amount of pathogens transported by DSE (viruses, bacteria, fungi, and infectious diseases), $\Psi$= Arid Zones, $\delta$= Population living in a climatic zone BW, $\gamma$= Climatic Change, $\omega$= Drought, unpaved roads, loose soil, unprotected surfaces and $\dot{u}$= Estimated deposits of toxic industrial emissions.

$$DEs = WV \times Du \times PM \{ \dot{\omega} \}, \quad (7)$$

Where Dust events (DEs) is defined by: $WV$= Wind Velocity, $Du$= Duration, $PM_{10}$= Particulate Matter and $\omega$= desertic factors.

$$PHO = \sum_{i=1}^{n} (\Phi, \chi, \dot{\omega}) \times Wi \{R + \delta\}^k \quad (8)$$

Where Projected Health Outcomes for 2030 – 2050 (PHO) is defined by: $\Phi$= SES, $\chi$= demographic factors, $\dot{\omega}$= DEs, $R$= Patient hospitalization, $\theta$= Exposure time to $PM_{10}$ and $K$= Degree of inflammation in the body. In this equation, PHO refers to the Projected Health Outcomes either for the present (2010-2014), or projections for 2030 and 2050 due to DEs: denotes the sum
of $\Phi = \text{SES}$, $\chi = \text{Congenital factors}$ and $\omega = \text{DSE}$; which affect the $R = \text{Patient hospitalization due to}$; $\theta = \text{Exposure time to PM}$; and may be exacerbated by $\phi = \text{risk of detrimental structural and cognitive effects, neurodegenerative as well as mental illnesses}$. Now we have a predictive model to analyze the health outcomes of dust events in a society with Köppen climate classification type BW.

Preliminary results of the investigation have found a preponderant value between the relationship between the location of patients in the metropolitan area of El Paso, TX and the correlation present between the age of patients and their income, which will allow explain how susceptible people are poorer and affected due to possible malfunction of their own houses and susceptibility, which may not be prepared for continuous events associated with DSE, which continuously affect patients (see Figure 2.10). A primary aspect of our developed model, is that it can adequately estimate the prevalence of a disease or group of diseases associated with a DSE considering its duration and frequency.

Spearman’s correlations indicate that dust events (events with high PM$_{10}$ and wind speed values) are significant associated to diagnosis with a $p$ value of 0.008. Figure 2.5 shows that from 2010-2014 there were more hospitalizations in a DE (62%) than in a regular day (RD) (38%). Figure 2.6 shows that during DE there were 61.47% more hospitalizations due to acute conditions; 62.67% more from chronic conditions and 63.98% more from mental health than in a regular day from 2010-2014. Figure 2.7 shows the increase in hospitalizations during 8 days after a DE and emphasized the possible effect of PM$_{10}$ exposure during these events and hospitalizations; the effect of a DE on hospitalizations might be highest during the actual day of the DE and such effect decreases after that.
Table 2. Comparison of ICD-9 diagnosis in a regular day and in a DE from 2010-2014

<table>
<thead>
<tr>
<th>ICD-9 diagnosis</th>
<th>no DSE</th>
<th>DSE</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3792</td>
<td>6375</td>
<td>10167</td>
</tr>
<tr>
<td>2</td>
<td>3899</td>
<td>6457</td>
<td>10363</td>
</tr>
<tr>
<td>3</td>
<td>4858</td>
<td>8177</td>
<td>13035</td>
</tr>
<tr>
<td>4</td>
<td>1295</td>
<td>2275</td>
<td>3571</td>
</tr>
<tr>
<td>5</td>
<td>5778</td>
<td>10111</td>
<td>15889</td>
</tr>
<tr>
<td>6</td>
<td>1665</td>
<td>3175</td>
<td>5040</td>
</tr>
<tr>
<td>7</td>
<td>11813</td>
<td>19653</td>
<td>31466</td>
</tr>
<tr>
<td>8</td>
<td>8834</td>
<td>14550</td>
<td>23384</td>
</tr>
<tr>
<td>9</td>
<td>11165</td>
<td>18833</td>
<td>29998</td>
</tr>
<tr>
<td>10</td>
<td>6040</td>
<td>10141</td>
<td>16181</td>
</tr>
<tr>
<td>11</td>
<td>15255</td>
<td>25830</td>
<td>42135</td>
</tr>
<tr>
<td>12</td>
<td>2041</td>
<td>3310</td>
<td>5351</td>
</tr>
<tr>
<td>13</td>
<td>4208</td>
<td>7429</td>
<td>11697</td>
</tr>
<tr>
<td>14</td>
<td>444</td>
<td>762</td>
<td>1206</td>
</tr>
<tr>
<td>15</td>
<td>866</td>
<td>1384</td>
<td>2230</td>
</tr>
<tr>
<td>16</td>
<td>4059</td>
<td>6625</td>
<td>10684</td>
</tr>
<tr>
<td>17</td>
<td>8005</td>
<td>13441</td>
<td>21446</td>
</tr>
<tr>
<td>19</td>
<td>17935</td>
<td>26980</td>
<td>40921</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>113210</td>
<td>187554</td>
<td>300764</td>
</tr>
</tbody>
</table>

The top 7 causes of admission during a DE from 2010-2014 are: causes of injury & poisoning (15.6%), complications of pregnancy, childbirth, & the puerperium (14%), diseases of the circulatory system (10.5%), diseases of the digestive system (10%), and diseases of the respiratory system (7.8%), diseases of the genitourinary system (5.4%) and mental disorders (5.3%) (Table 2.2 and Figure 2.8).

Table 2.3 shows the top high-risk reasons for hospitalizations, aside from deliveries, respiratory (pneumonia, obstructive chronic bronchitis, asthma) mental (unspecified episodic mood disorder, cerebral artery occlusion, unspecified with cerebral infarction, schizo-affective type schizophrenia unspecified state); cardiovascular (other chest pain, coronary atherosclerosis of native coronary artery, atrial fibrillation); and infectious (urinary tract infection, acute
pancreatitis, acute appendicitis without mention of peritonitis) which are affected by bacteria, virus, or due to inflammation.

More patients live in areas with more roads and DE shows to affect the population with all incomes but more frequent patients with a family income of <40,000 dollars; and there are more cases of single born in areas with low income at El Paso, TX from 2010-2014 (Figure 2.10). There are 59.5% more females hospitalized than males (40.5%) during 2010-2014 at El Paso County (Figure 2.9).

Figure 2.5 Comparison of total hospitalizations in regular Days and DE from 2010-2014. There were more hospitalizations in a DE (62%) than in a regular day (RD) (38%).
Figure 2. Comparison of Acute, Chronic and Mental total Admissions code in a DE vs a regular day. During DEs there were 61.47\% more hospitalizations due to acute conditions; 62.67\% more from chronic conditions and 63.98\% more from mental health than in a regular day from 2010-2014.
Figure 2. Total Hospitalization percentage per day before and after DE (each day has many hospitalizations) from 2010-2014. There is an increase in hospitalizations after a DE and emphasized the possible effect of PM$_{10}$ exposure during these events and hospitalizations; the effect of a DE on hospitalizations might be highest during the actual day of the DE and such effect decreases after that.
Figure 2.8 Comparison of total IDC-9 Admissions code in a DE vs a regular day from 2010-2014. The top 7 causes of admission during a DE from 2010-2014 are: causes of injury & poisoning (15.6%), complications of pregnancy, childbirth, & the puerperium (14%), diseases of the circulatory system (10.5%), diseases of the digestive system (10%), and diseases of the respiratory system (7.8%), diseases of the genitourinary system (5.4%) and mental disorders (5.3%).
### Table 2. 3 List of most frequent ICD-9 diagnosis during DEs due to high-risk Respiratory, Mental, Cardiovascular and Infection causes from 2010-2014.

<table>
<thead>
<tr>
<th>Top reasons for hospitalizations</th>
<th>ICD-9</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Respiratory</strong></td>
<td></td>
</tr>
<tr>
<td>Pneumonia, organism unspecified</td>
<td>486</td>
</tr>
<tr>
<td>Obstructive chronic bronchitis with (acute) exacerbation</td>
<td>491.21</td>
</tr>
<tr>
<td>Asthma, unspecified type, with (acute) exacerbation</td>
<td>493.92</td>
</tr>
<tr>
<td><strong>Mental</strong></td>
<td></td>
</tr>
<tr>
<td>Unspecified episodic mood disorder</td>
<td>296.90</td>
</tr>
<tr>
<td>Cerebral artery occlusion, unspecified with cerebral infarction</td>
<td>434.91</td>
</tr>
<tr>
<td>Schizo-affective type schizophrenia unspecified state</td>
<td>295.90</td>
</tr>
<tr>
<td><strong>Cardiovascular</strong></td>
<td></td>
</tr>
<tr>
<td>Other chest pain</td>
<td>786.59</td>
</tr>
<tr>
<td>Coronary atherosclerosis of native coronary artery</td>
<td>414.01</td>
</tr>
<tr>
<td>Atrial fibrillation</td>
<td>427.31</td>
</tr>
<tr>
<td><strong>Infection</strong></td>
<td></td>
</tr>
<tr>
<td>Urinary tract infection, site not specified</td>
<td>599.0</td>
</tr>
<tr>
<td>Acute pancreatitis</td>
<td>577.0</td>
</tr>
<tr>
<td>Acute appendicitis without mention of peritonitis</td>
<td>540.9</td>
</tr>
</tbody>
</table>
Figure 2.9 Comparison of total hospitalizations by Female, Male and Unknown in a RD and in a DE from 2010-2014. There are 59.5% more females hospitalized than males (40.5%) during 2010-2014 at El Paso County.
Figure 2. 10 Map of cases of single born by cesarean section during DEs at El Paso, TX from 2010-2014. More patients live in areas with heavily trafficked roads and DE shows to affect the population with all incomes but more frequent patients with a family income of <40,000 dollars; and there are more cases of single born in areas with low income at El Paso, TX from 2010-2014.

Conclusions and Future Work

Several studies have tried to explain the most relevant aspects of the adverse outcomes of DEs in climates type BW, however none had proposed a reliable model associated with the numerical prediction of the present and projected impacts for 2020 and 2050. This research discusses a multifactorial problem, which requires a multivariate analysis which will be elaborated in the following research phase. In addition, we will Investigate whether dust exposure to PM$_{10}$
during a DE (day of and 7 days after) between 2010 and 2014 is associated with hospital admissions due to acute or accelerated disease progression of neurodegenerative diseases (Parkinson’s, Alzheimer’s, and Huntington’s), mental illness (depression and anxiety) and OD (e.g., respiratory, cardiovascular, infectious diseases and top diagnosis significantly associated by DE -diagnosis listed in the ICD9) in El Paso, TX. In addition, we will look into the biological plausibility of these diseases in order to establish a cause-and-effect relationship between PM$_{10}$ during a DE and each significantly associated disease.
References


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Chapter 3: Intelligent Tool for Decision Making Associated with Hospitalization and Sandstorms for the Optimization of Ambulances
Chapter 3
Intelligent Tool for Decision Making Associated With Hospitalization and Sandstorms for the Optimization of Ambulances

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ABSTRACT

The shortest path problem is a typical problem of optimization. This chapter presents an innovative model associated with the use of case-based reasoning to solve a problem of routing vehicles in a Hospital of El Paso, United States. In this chapter, diverse components are described to characterize this problem through the use of a knowledge system. The algorithm was developed in Java, thus obtaining a tool which determines the best tracks to the vehicles associated with ambulances. An experiment was realized to probe the validations; the results were used to compare it with the Dijkstra algorithm and determine the quality of the results. The future research of this intelligent tool is to determine an innovative perspective related to episodic knowledge applied to resolution of diverse ambulances, and as this topic is determinative to find and remember the best solutions quickly, additionally the authors compare it with a code from other postgraduate students trying to implement an algorithm similar to logistics but using a shuffled frog leap algorithm.

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Intelligent Tool for Decision Making Associated with Hospitalization and Sandstorms for the Optimization of Ambulances

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ABSTRACT

The shortest path problem is a typical problem of optimization. This chapter presents an innovative model associated with the use of case-based reasoning to solve a problem of routing vehicles in a Hospital of El Paso, United States. In this chapter, diverse components are described to characterize this problem through the use of a knowledge system. The algorithm was developed in Java, thus obtaining a tool which determines the best tracks to the vehicles associated with ambulances. An experiment was realized to probe the validations; the results were used to compare it with the Dijkstra algorithm and determine the quality of the results. The future research of this intelligent tool is to determine an innovative perspective related to episodic knowledge applied to resolution of diverse ambulances and as this topic is determinative to find and remember the best solutions quickly, additionally the authors compare it with a code from other postgraduate students trying to implement an algorithm similar to logistics but using a shuffled frog leap algorithm.

1. Introduction

Dust storms are recurring weather effects in a BW climate in the Köppen climate classification, where the city of El Paso, in Texas, is located and affects about one million people, in a database obtained by DSHS and associated with 299,804 records compiled in different events of four years. Each patient hospitalized in the main hospital of the city of El Paso and linked to at least 127 diseases whose involvement is associated with this type of weather events, it is crucial
to know this for this research project, each of the scenarios that occur each time a dust storm occurs in order to adequately link a requirement of a set of ambulances for the population at risk during this climatological event and that is recurrent during the minus seven months of the year.

Nowadays, digital maps are increasingly common to greatly improve the optimization of evacuations performed by emergency vehicles such as ambulances or fire trucks. With the progress that has been made in technology, these maps are becoming more sophisticated, in the way that they are able to find specific locations, draw routes and so forth [16]. Another thing that is noteworthy is that they show how the information has improved dramatically, as they changed from traditional maps to maps with real images taken from the air, satellite, or even a hybrid version of these two. The motivation of this project is specifically focused on the use of this increased interaction nowadays, in order to achieve an improvement in the logistics after a huge dust storm which affects many people and determine what is the best way to organize the ambulances to move patients to diverse hospitals [18]. The objective of this work is to develop a system to help create routes on the basis of the emergencies given in El Paso, Texas, through the use of a system of neighborhoods of ants that allows them to create routes to take care of patients affected by a dust storm or other types of emergencies in a quick way. This is important because the life of the people is at risk. In the United States, to minimize the time to arrive to the place of the accident, they do a comparison according to three possible emergencies at the same time and require other vehicles to respond to them. To provide assistance to citizens, paramedics in an ambulance need a route to arrive as quickly as possible to the place of the incident [17]. If there are many emergencies, they are classified in order of importance: Hospitalization related to a dust storm, Rescue, and Prevention Action on public hazard. In all these activities, the time is vital because with a timely arrival the effect of the damage in a dust storm can be decreased to prevent
an explosion in the leak case and find alive persons among others. The bio-inspired algorithms are a technique of artificial intelligence focused on the solution of different problems, especially optimization problems. One of these algorithms is the swarm intelligence algorithm, where we can find the algorithm of the ant colony (ACO), particle swarm optimization (PSO), bees and so on [19]. The proposed algorithm to solve the routing problem in El Paso city is an Ant Colony System.

2. Descriptions of the Model Components

In this section, we offer details of each component related to the application domain that is involved in the problem, in our case we solve a Logistics problem related to the El Paso Health System’s Hospitals by the use of a bioinspired algorithm to create routes of vehicles to attend emergencies.

2.1 The Shortest Route

The problem known as the shortest path or the shortest route, as its name suggests, tries to find the minimum or shortest route between two points. This minimum may be the distance between origin and destination points or the time to travel from one point to another. Mathematically, this system is described as a weighted graph $G = (V, A, d)$ where vertices are represented by $V = \{V_0, V_1, ..., V_n\}$, and arcs are represented by $A = \{(v_i, v_j) \mid i \neq j\}$. The distances associated with each arc are represented by the variable $C_{ij}$ measured by the Euclidean distance. The objective functions of the problem [7] are:

$$minZ = \text{All the defined arcs } C_{ij}X_{ij}$$

(1)
Decision variables are as follows:

- $X_{ij}$: action to move from node i to node j. 0 indicates that there is no displacement and 1 indicates that yes there is movement.

- $C_{ij}$: cost or time to get from node i to node j.

- Restrictions for the Total input flow = total output flow (external input into node j) + i All the defined arcs $(i,j) X_{ij} \leq$ (external output from node j) + k All the defined arcs $(j,k) X_{jk}$

This type of optimization problems cannot be solved using exact methods. We cannot find its optimal solution with acceptable computational efforts. Since the early 50s, many algorithms have been developed to find a solution to this problem by finding good solutions but not necessarily optimal solutions. In the 80s, the solution techniques focused on the implementation of general-purpose metaheuristics including, among others, the ant colony, genetic algorithms, and taboo search.

2.2 The Shortest Path Algorithm

The shortest path algorithm, also called the Dijkstra algorithm, is an algorithm for determining the shortest path given in a source vertex to other vertices in a directed graph with weights on each edge. The shortest path algorithm belonging to the greedy algorithm [9] is an efficient algorithm of complexity $O(n^2)$, where n is the number of vertices, used to find the least cost path from a source node to all other nodes in the graph. It was designed by the Dutchman Edsger Wybe Dijkstra in 1959 [13]. The foundation on which this algorithm sits is the principle of optimality; the solution is built with the election of local optima in the hope of obtaining a global optimum.
3. Proposal Methodology

It is important to define that among a plethora of artificial intelligence techniques, the most appropriate one and the one that was selected for the present research was combined Case-based Reasoning and Ant Colony Optimization algorithm to improve a correct solution, which was validated with other similar investigations.

The internal structure of the RBC systems is composed of two parts: the obtaining of the case and the reasoning of the case (Shiu et al., 2004). The first is responsible for finding the appropriate cases in the base of cases and the second is responsible for finding a solution to the problem given its description. (See Figure 3.1).

The RBC fulfills a cycle from the beginning of the problem until the solution is obtained, the cycle covers four parts: recover, reuse, review and retain (see Figure 3.2). This is also known as the 4 Rs (Retrieve, Reuse, Revise and Retain), according to Pajares et al. (2010). The parts that comprise the RBC cycle depend on the case base or case library since in this case the previous cases that contain valuable information are stored for the RBC to be successful. We must remember that cases are problems that have a solution, for that it is necessary to obtain a representation of the cases so that they are stored in the base of cases since not all the information that is available about the problem is important to solve the problem. For this reason, we add one more part to the RBC that is the representation of cases.

Case representation: It is one of the most important parts of the RBC because the four parts of the RBC life cycle depend on it. Its importance lies in the fact that a case is a piece of knowledge that represents an experience and includes a problem, which is the description of the task to be solved (Pajares et al., 2010) and a solution, which corresponds to how the task was solved (Pajares et al., 2010). In turn, a set of cases is called case base or case library. Usually, a
case is represented as an attribute-value pair; this represents the problem and the solution of the case. For Behbahani et al. (2012) in some cases, the case contains a third element that is the result, that is, the state of the problem once the solution was applied. The experience can be represented in a different way; the classic one includes vector form, frame-based, object-oriented and textual, although there are already more sophisticated representations that are hierarchical cases, generalized cases, cases based on the based design, cases based on planning (Bergmann et al., 2005).

Recover cases: The quality in the result of the RBC systems depends on the similarity measures used for the recovery of similar cases. The soft computing techniques used in this part of the RBC are:

![Figure 3.1 Basic structure of an RBC system according to Shiu et al. (2004).](image-url)

Figure 3.1 Basic structure of an RBC system according to Shiu et al. (2004).
diffuse indexing, diffuse grouping, case classification, probability, Bayesian models for the selection of cases (Shiu et al., 2004), the nearest neighbor (Li et al., 2009). In this phase, the current problem is checked against the problems stored in the base of cases. For Behbahani et al. (2012) the comparison is a process of comparing two cases among themselves and determining the degree of similarity (DOS, for its acronym in English degree of similarity). Besides the measures of similarity, knowing the domain helps determine the similarity of the new case with a previous case and having the degree of similarity lead us to a degree of adequacy of the solution of the problem or current case (Begum et al., 2011).

**Reuse cases:** The reuse can be given by means of copying or integrating the solution of the cases that were recovered in the previous part. In reuse, interactive and conversational diffuse reasoning can be used, learning to reuse case knowledge and diffusional approaches (Shiu et al., 2004). This part is also known as adapting the solution since the solution that was obtained in some occasions is necessary to adapt it to be given a solution to the case, as explained by Begum et al. (2011) and Shiu et al. (2004).
3.1 Case-Based Reasoning to Solve Route Problems

There are three forms of adaptation that are the most used: substitution, transformation, and generative adaptation, this is indicated by Pajares et al. (2010).

Review cases: The evaluation of the solution originated in the reuse of the case is carried out, this is usually carried out by domain experts. In case the solution needs some modification, this is done in this phase, and it is called repair. Must remember that the success or failure of the solutions originated is useful information to improve the RBC (Pajares et al., 2010). The techniques used here are neural networks and evolutionary approach, rules of adaptation using set theories.

Retain cases: Then the new case or problem and its solution are retained or stored in the base of cases for future use (Begum et al., 2011), that is to say, that the solution was already confirmed or validated by domain experts. The decision whether the new case is stored in the case base also depends on how useful the knowledge of that case will be in the future (Pajares et al., 2010). The techniques that can be used in this part are fuzzy rules, neural networks, set theory (Shiu et al., 2004). This learning is incremental, thus we must bear in mind that the more cases stored in the database, the RBC will increase, as it will reach the time needed to maintain the database, and continues fulfilling its function (Pajares et al., 2010). Many authors described different applications to resolve this kind of problem. Lianxi Hong proposed an algorithm which permits to determine the time to reach a specific point in a city according to different possible scenarios [8]. On the other hand, Lei, Laporte & Guo (2011) proposed a concept similar to ours, with relation to “emergencies,” which may occur in any time and place [11], and organize the demand to the vehicles, in our case is to the rescue units, try to minimize the effort to attend the
demands in a day with the estimation of arrive, and solve another emergence, for example bee swarm which can be damage to children (Figure 3.3).

Figure 3. 3 An ambulance in a transport model in a Smart City.

4. The Proposed Model of our Hybrid Algorithm.

An intelligent tool was developed using Case-based Algorithm based on Ant Colony Algorithm and the programming language Java (J2SE) and as the first step we begin with the creation of the graph for the central area covering the Main Hospital in El Paso, a total of 2451 streets, avenues and boulevards (edges) and 1710 nodes. Subsequently, an entity was designed called “object” to store information about each node, as the impact to neighboring nodes and their respective distance. These objects were related to a data structure called a multidimensional array which saves computer resources because this structure does not cause the overflow of memory.
related with the cells which compound the grid and generate a square incidence matrix, it stores only the necessary track which is visualized in their analysis.

The Ant Colony algorithm has been proved effective to solve NP-Hard problems when they use multidimensional arrays [2]. The structure of the generic algorithm is as follows [5]:

The optimization quantity is the distance of the route. Thus, the truck movement cost between loading spots i and j is a function of all separate costs for each factor which affects the track route:

\[
d_{ij} = oc_{aij} + \beta d_{bij} + \gamma dc_{ij} + \ldots
\]  

Let \( t_{ij}(t) \) be the intensity of trail on edge (i, j) at time t. Each ant at time t chooses the next node, where it will be at time \( t + 1 \). Therefore, if we call an iteration of the ACO algorithm the n moves carried out by the n ants in the interval \( (t, t +1) \), then for every n iteration of the algorithm, each ant has completed a tour. At this point the trail intensity is updated according to the following formula:

**Algorithm 1. Optimization based on Ant Colony**

Initialize parameters

while not stop condition

for ant = 1 to n construct solution

evaluate solution

update pheromones

end

end while

\[
\tau_{ij}(t + n) = \rho \cdot \tau_{ij}(t) + \Delta \tau_{ij}
\]

where \( \rho \) is a coefficient that represents the evaporation of trail between \( \Delta \tau_{ij} = m. \)

\[
k = l \Delta \tau_{kij}
\]
\[ d_{ij} = ad_{ij} + \beta db_{ij} + \gamma dc_{ij} + \ldots \] (3)

The coefficient \( q \) must be set to a value < 1 to avoid unlimited accumulation of trail (see note 1).

In our experiments, we set the intensity of trail at time 0, \( t_{ij} (0) \), to a small positive constant \( c \). In order to satisfy the constraint that an ant visits all the \( n \) different loading spots, we associate with each ant a data structure called the \( h \)-list, that saves loading spots already visited up to time \( t \) and forbids the ant to visit them again before \( n \) iterations (a tour) have been completed. When a tour is completed, the \( h \)-list is used to compute the ant’s current solution (i.e., the movement cost of the path followed by the ant). The \( h \)-list is then emptied, and the ant is free to choose again,

\[ \tau_{ij} (t + n) q \tau_{ij} (t) + \Delta \tau_{ij} \] (4)

\[ k = l \Delta \tau_{ki} \] (5)

\[ \eta_{ij} = 1/d_{ij} \] (6)

We call visibility \( h_{ij} \) the quantity \( 1/d_{ij} \). This quantity is not modified during the run of the AS, as opposed to the trail, which instead changes according to the previous formula (4). We define the transition probability from loading spot \( i \) to loading spot \( j \) for the \( k \)th ant as

\[ p_{kij} = \tau_{ij} (t) \alpha \eta_{ij} \beta k \in \text{allowed } k \tau_{ik} (t) \alpha \eta_{ik} \beta \] (7)

The software implements the ability to block and alter the meaning of the streets, a fact that occurs in the central city of El Paso because of events, accidents, public works and so on. The method Initialize parameters enters the source node, the destination node, blocked streets and the number of ants involved in the search for the solution similar to the proposal in (Xiong, Wang & Yan, 2007). Construct solution takes place when ants move randomly with both probabilities using
the Monte Carlo method if there is already a trail of pheromone. Once an ant has found the evaluate solution, the destination node determines if the journey is of good quality, discarding those paths that do not decrease the distance obtained by other ants, and updating the pheromone if you have found a shorter route.

The user interface displays the found routes to the destination, with the option of display all of them or one in particular in a map (see Figure 3.4), which has the options of adding landmarks (churches, schools, hospitals, parks, rivers), zoom, viewing the different layers, storing in the route file, exporting the map as an image and sending it via Bluetooth to a mobile device.

5. Experimental Results

The proposed algorithm was compared to the algorithm of Operations Research: The shortest path (Dijkstra). The comparison was carried out with the generation of 20 runs starting from the central zone associated with El Paso Hospital (node 759) to different nodes (see Table 3.1).

Figure 3.4 Drawing of a single route (left) and drawing of five routes (right).
Figure 3. 5 ACO and Case-based Reasoning and Dijkstra comparison.

Table 3. Result for each ambulance travel from the houses of the patients to a Hospital in El Paso.

<table>
<thead>
<tr>
<th>#</th>
<th>Origin</th>
<th>Destination</th>
<th>Dijkstra</th>
<th>Hybrid Algorithm</th>
</tr>
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<tr>
<td>1</td>
<td>945</td>
<td>759</td>
<td>222</td>
<td>212</td>
</tr>
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<td>9</td>
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<tr>
<td>20</td>
<td>1199</td>
<td>759</td>
<td>885</td>
<td>984</td>
</tr>
</tbody>
</table>

The results were obtained with $\mu = 25.15$ seg and $\sigma = 15.65$ seg in 35% of cases. While the Ant Colony gives better results than the shortest path algorithm (1, 4, 7, 10, 11, 14 and 18), in 20%
the results were similar (8, 9, 12 and 17) and 45% was surpassed by the shortest paths as in Figure 3.7. We select from a list of 1487 sickness related with the effects of a Dust Storm, two incidences and with a Kriging Model used in ArcGIS, determine the expected value of patients that required an ambulance to travel to Hospital, as it is shown in Figure 3.6.

Another comparison was using the same instances and information obtained from Table 3.1 of twenty different ambulances from El Paso Health System’s Hospitals, with the intention of building a robust design of experiments to try to understand the accumulative number of optimal solutions to reach the best track using the search space to three different codes of Hybrid Algorithm, ACO and Cultural Algorithm. The results will be observed in Figure 3.7.

6. Conclusion and Future Research

The algorithm currently implemented gives good quality solutions to an NP-hard problem, improving by 35% of cases the routes provided by the shortest path algorithm. The 45% where the shortest path algorithm exceeds the ACO which is attributed to not yet implementing the evaporation of the pheromone, the pheromone amount in nature may remain a few hours to several months depending on different aspects, such as ant species or soil type [7], causing a minor influence on the effect of evaporation in the process of finding the shortest path. Due to the long persistence of the pheromone, it is difficult for the ants to “forget” a path that has a high level of pheromone but have found a path even shorter.
Figure 3.6 Incidence of a specific sickness in Neighborhoods of El Paso, and a Kriging Model of incidence of this sickness in the future with the necessity of more ambulances to transport more patients during a Dust storm.

Figure 3.7 Comparative analysis of a Hybrid Algorithm, a PSO and a Cultural Algorithm for an instance of three emergencies associated with a Dust Storm at the same time, when we consider its performance on the basis of Table 3.1.

Another comparison was using the same instances and information obtained from Table 3.1 of twenty different ambulances from El Paso Health System’s Hospitals, with the intention of building a robust design of experiments to try to understand the accumulative number of optimal solutions to reach the best track using the search space to three different codes of Hybrid Algorithm, ACO and Cultural Algorithm. The results will be observed in Figure 3.7. Keep in mind
that if this behavior is transferred to the computer to design a search algorithm sometimes, it can converge quickly to the local optimum. In this section, the results of the trial are presented. First of all, the data collection and the measurement of variables are described.

Figure 3. 8 Using Bluetooth, it is possible to use our proposed model of ambulances in a huge contingency related to a Dust storm.

Based on the results obtained, we recommend the implementation of heuristic algorithms such as ant colony, which have demonstrated to do well on a variety of problems [3,4]. As future work, it would be important to implement the evaporation of the pheromone, find benchmarks that are being used at international level and prove to those instances of the problem, replicate the project using Java (J2ME) for the system to operate on mobile devices which provide advantages to the system in units of El Paso Health System’ Hospitals. Making an Intelligent Tool requires Access from any device including cellphones with different screen size and reorganizing the correct decisions in a mobile device as is shown in Figure 3.8.

We decide to make a comparison of our algorithm with relation to a PSO Algorithm and a Cultural Algorithm. We discovered the proposal of combining Case-based Reasoning and ACO Algorithm to obtain three different paths to a successful number of emergencies occurring at the
same time, and that its performance improves by 22% the performance of PSO Algorithm and by 37% the performance of Cultural Algorithms. In the future research, it is important to describe the different times in other quadrants (the city is divided into four regions named Quadrants) of the city in the border zone which covers Hospitals and covers only the 48.7% of territorial space of the city.
References


Chapter 4: Associations Between Exposure to Air Pollution After a Dust Event and Hospitalizations in El Paso, Texas, USA

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Abstract.

It has been demonstrated that exposure to increased levels of airborne particulate matter (PM) can increase the susceptibility to respiratory, circulatory, mental and other diseases due to inflammation. In addition, living in an arid city with frequent high levels of PM due to Dust Exposure (DE) could have a negative impact on population’s health. This study assesses the relationship between DE of 100µg/m³ increments in maximum PM₁₀ and/or 10mph daily maximum wind speed increase and hospital admissions with different lag structures, including a single-day lag (current day [lag0]), and the following 1-7 day ([lag1- lag7]) in El Paso, TX. The regression model assuming an overdispersed Poisson distribution was used, and the relative risk rate was estimated. Results indicate that hospitalizations due to Valley fever, Coronary Atherosclerosis, Genitourinary Diseases, Neurodegenerative Diseases, Injury and Poisoning, Chemotherapy, Septicemia, Aftercare services, Circulatory System Diseases, Injury and Poisoning, Respiratory System Diseases Associated Diseases, births, and all ICD-9 categories were significantly positively associated with DE, listed from higher to lower risk, at various lags. Valley fever has the highest hospitalization risk (Relative risk [RR] of 1.468). The second highest association is with Coronary Atherosclerosis (RR of 1.136) followed by Genitourinary Diseases (RR of 1.056) and Neurodegenerative Diseases (RR of 1.051).

Keywords: Blowing dust events, Quasi-Poisson Regression Analysis, Pattern Recognition, Health Effects, Neurodegenerative disorders and Mental illness.
Introduction

Desert dust is a major natural particulate matter (PM) contributor to air pollution worldwide (Dadvand et al., 2011; Ahmed et al., 2020). Dust can be transported worldwide from arid and semi-arid regions where loose soil can easily be lifted during high wind speeds (Lim & Chun, 2006). Blowing dust activity is a frequent event in El Paso, Texas, located in the Chihuahuan Desert, one of the major dust source areas in the Western Hemisphere (Prospero et al., 2002). Residents are exposed to these dust events throughout the year, and the dust can penetrate indoors and can be enriched with potentially hazardous metals and other pollutants (Van Pelt et al., 2020). Within a day, atmospheric PM$_{10}$ (particulate matter with mean aerodynamic diameter 10 micrometers or smaller) levels in El Paso, TX often display marked peaks that lead to very high acute doses of PM$_{10}$ (Staniswalis et al., 2005).

The literature suggests that exposure to coarse particle air pollution (as PM$_{10}$) over time can lead to serious health problems, including myocardial infarction (Wolf et al., 2015), respiratory diseases, asthma, lung cancer (Tarhan et al., 2016 & Vineis et al., 2004), diabetes (Chan et al., 2018), neurodegenerative and neurological disorders (Heusinkveld et al., 2016 & Kioumourtzoglou et al., 2015), impacts on the central nervous system (Block et al., 2012), prevalence of chronic kidney disease and reduced renal function (Yang, et al., 2017), fungal infections such as Valley fever (Tong et al., 2017), and even death after either acute or chronic exposures (Carinanos et al., 2007).

Studies in the Chihuahuan Desert indicate that respiratory diseases (Grineski et al., 2011) and cardiovascular diseases (Rodopoulou et al., 2014) are associated with high concentrations of particulate matter from dust events. Pneumonia with septicemia is associated with interquartile increments in the levels of PM$_{10}$ lag 0 with increments of 21.61% in the number of ED visits during
the warm season (Cheng et al., 2019). These diseases share common inflammation features (Olvera, 2018 & Saydoff et al., 2005) which could be caused by excitotoxicity and oxidative damage due to exposure to high levels of airborne particulate matter (Mohan Kumar et al., 2008 & Peixoto et al., 2017). A significant association between PM$_{10}$ and daily mortality has previously been found in El Paso, TX. Staniswalis et al. (2005) determined that 10 µg/m$^3$ increase in the daily average PM$_{10}$ corresponds with a 2.06% increase in mortality 3 days after a PM increment.

While there are many studies that have sought to examine the effects of anthropogenic/urban (industry, motor vehicle, and combustion by-products) sources of PM on human health, far fewer studies have considered contributions from natural sources, especially due to PM$_{10}$ exposure (Morman & Plumlee, 2014) and in the Chihuahuan desert of USA. Due to the high concentrations PM$_{10}$ during dust events at El Paso Texas (Rivera Rivera et al., 2010), it is necessary to determine if there is a frequency of hospitalizations due to exposure to high concentrations of PM$_{10}$ and wind speed (a surrogate variable of windblown dust) so residents and public health and emergency management authorities can be informed of these possible negative health effects during and after dust exposures.

**Background**

**PM$_{10}$ in El Paso, Texas**

Blowing dust activity is a very common meteorological event in El Paso, Texas, the largest city in the U.S. portion of the Chihuahuan Desert. The northern Chihuahuan Desert is the one of the most significant sources of dust in the Western Hemisphere (Prospero et al., 2002), with agricultural lands, ephemeral lakes, and dry river floodplains identified as the main sources of the dust from this desert that is blown into El Paso, Texas (Baddock et al., 2011, Lee et al., 2009, &
Dust particles at El Paso are dominated by quartz (Rivas, 2019), which is a form of crystalline silica, in itself recognized as a health hazard (Ghio et al. 2014). Based on data collected at the El Paso International Airport (KELP) from 1932 through 2005, dust events in El Paso occur on average 15 times a year, primarily between December and May, and last an average of ~2 hours each (Novlan et al., 2007), thus providing a short-term acute exposure to particulate matter. The frequency of these dust events in the Southwestern USA has increased (Tong et al., 2017) and will continue to rise as climate changes (Schweitzer et al., 2018). Therefore, exposures to dust events and their particulate matter are likely to be an increasing hazard to human health in El Paso.

The Paso del Norte (PdN) air quality basin includes three cities: El Paso, TX; Sunland Park, NM; and Ciudad Juárez, Chihuahua, Mexico. In addition to desert dust, this region experiences unhealthy levels of particulate matter from other sources (exceeding the national ambient air quality standards (NAAQS)), with road dust from unpaved roads being the most important contributor (Li et al., 2001 & TCEQ, 2021). It was calculated that the PM$_{10}$ road dust emissions were the highest in Ciudad Juárez and increase by a factor of five with the highest emissions in Spring (Kavouras et al., 2016). About 50% of Ciudad Juarez streets are unpaved, and the city has extensive areas of bare soil, able to lift up during a strong wind (Kavouras et al., 2016 & Rodopoulou et al., 2014). The prevailing wind direction during a dust event in El Paso is westerly and southwesterly (Novlan et al., 2007 & Rivera Rivera et al., 2009) – crossing zones of known dust source areas in the desert (Baddock et al., 2011), and favoring the transport of dust from Cd. Juarez into El Paso. These conditions provide El Paso residents fast exposures to potentially hazardous concentrations of dust particulate matter (Rivera Rivera et al., 2010) on dry windy days. For example, an air monitoring station in El Paso indicated peak hourly PM$_{10}$ values during DEs
of 1955.2 μg/m³ on February 20, 2013 (Rivas et al., 2014), and maximum hourly PM$_{10}$ of 4739.3μg/m³ and wind speed of 28.4 mph with a visibility of 0.3 miles on March 18, 2012.

**Coarse Particulate Matter Associations with Disease**

Neurodegeneration, dementia, and mental health represents a significant and rising challenge to public health (Chen, 2021, Medical Research Council, 2021, & WHO, 2021). Neurodegenerative diseases including Alzheimer's disease (AD), Parkinson's disease (PD), and Huntington's disease (HD) (Kiaei, 2013) share common neurodegeneration and neuroinflammation features (Perl et al., 1998, & Saydoff et al., 2005). The nervous system can be affected by neurodegeneration caused by excitotoxicity and oxidative damage due to exposure to high levels of PM (Mohan Kumar et al., 2008 & Peixoto et al., 2017) causing an inflammatory episode in the brain tissue leading to migration of cytokine cells into the brain (Crotti & Glass 2015 & Olvera et al., 2018). A study indicated that with every 19.4 μg/m$^3$ of PM$_{10}$ there is an 7.2% increase in the risk of emergency visits for depressive episodes (Szyszkowicz et al., 2009). Short-term exposure to PM$_{10}$ is associated with light sleep and depression (Kang et al., 2021) and suicide (Braithwaite et al., 2019).

The genitourinary system has been found to be negatively associated with exposure to high levels of particulate matter by damaging renal function and by causing chronic urologic diseases through vascular damage and oxidative stress. PM constituents that cause renal toxicity, such as lead, cadmium, arsenic, and crystalline silica -as found in El Paso soil and dust (Rivas, 2019 & Van Pelt et al., 2020)- result in renal tubular or interstitial damage (Kim, 2017). Particles <10 μm in diameter can penetrate the nasal cavity to reach the alveoli, thus reaching the lungs and escaping into the blood stream (Xu et al., 2016), causing an inflammation or oxidative stress in the
microenvironment damaging the inner cellular lining of arteries. An increase of 10 μg/m³ in the PM_{2.5} concentration was associated with 14% higher odds for membranous nephropathy (Xu et al., 2016).

Exposure to PM_{10} during pregnancy has been suggested as a risk factor for pre-term birth during the last two months of pregnancy (Relative risk of 1.02–1.13 per 10 μg/m³ increase for last four weeks before delivery; 1.09; 1.02–1.15 for last six weeks before delivery; 1.10; 1.03–1.17 for last eight weeks before delivery) (Zhao et al., 2015). C-reactive protein, a biomarker of systemic inflammation, has been reported to increase the risk of preterm delivery. Exposure to high levels of PM_{10} has been associated with increased C-reactive protein concentrations in early pregnancy, suggesting that high levels of PM_{10} contribute to inflammation and thereby possibly to adverse pregnancy outcomes (Lee et al., 2011).

In addition to the inorganic particulate matter contained in the dust, there are substantial quantities of microorganisms (Zhang et al., 2016), which are potentially pathogenic (Weil et al. 2017), such as the spores of *Coccidioides* sp., the fungus that causes Valley fever (coccidioidomycosis) (Tong et al., 2017). Valley Fever is endemic to the arid areas of southwestern United States, Mexico, and Central and South America. In USA, the infection is most prevalent in southern Arizona followed by parts of California, Nevada, Utah, southern New Mexico, and southwest Texas (ADHS, 2016). The incidence of Valley fever increased eight-fold from 1998 to 2011 (CDC, 2013). In California and Arizona, precipitation and wind are the most important predictors of coccidioidomycosis incidence risk and explain up to 76% of the variability in fall valley fever incidence (Tong et al., 2017 & Weaver & Kolivras, 2018).
Health Disparities

In many societies, income is a determinant factor for a person to go to the hospital for a medical condition. Families with high income are more likely to take their children to the doctor or keep them at home on highly polluted days (Hofflinger & Boso, 2021). A USA-based study indicated that high concentrations of PM$_{2.5}$ affect people in poverty with a 1.35 times higher burden than the overall population (Mikati et al., 2018). Health disparities also impact mental health: individuals who suffer from mental illness have lower Social Economic Status (SES) than those who do not (Sareen et al., 2011). Those who have mental illness are more likely to be poor; the stress of being poor increases the risk of mental illness (Hudson, 2005 & Weissman et al., 2005).

Aims

The two aims of this study are to investigate whether increments of 100μg/m$^3$ increments in maximum daily hourly average PM$_{10}$ and/or 10mph daily maximum wind speed measured in El Paso, Texas (hereafter designated a dust exposure, DE) increase the day of and 7 days after association with hospital admissions by Codes from the International Classification of Diseases, Ninth Revision (ICD-9) category and hospitalizations due to neurodegenerative diseases (ND; Parkinson’s, Alzheimer’s, and Huntington’s), mental illness (MI; depression and anxiety), Valley Fever (VF), Asthma, Coronary Atherosclerosis, and other associated diseases which is the aggregated effect of the most frequent hospitalizations associated with at least 5% of hospitalizations and independently (AD; Births, Respiratory System Diseases, Circulatory System Diseases, Digestive System Diseases, Genitourinary System Diseases, Encounter for antineoplastic Chemotherapy, Unspecified Septicemia, Other Chest Pain, Dehydration, Cellulitis and Abscess of Leg, Osteoarthritis, Diabetes Mellitus, and Mental Disorders) and all-ICD-9-
category diagnosis in the county of El Paso, TX over a five-year period from 2010-2014 (see table 4.1); and to determine if demographic variables (age, and socio-economic status indexed by income, and education level) for each patient address Census Block Group (CBG) moderates the association between the defined elevated exposure of PM₁₀ and/or wind speed (day of and 7 days after) and hospitalizations in El Paso County, Texas. It will be determined if DE is associated with diseases admission among ND, MI, VF, Asthma, Coronary Atherosclerosis, AD and all ICD-9 category; and if any detected statistically significant increases in incidence of certain diseases were moderated by age, and by SES indexed by income, and education level.

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<thead>
<tr>
<th>Table 4.1 ICD-9 codes hospitalizations admissions for ND, MI, VF, Asthma, Coronary Atherosclerosis, High frequency ADs and ICD-9 category in El Paso, TX.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neurodegenerative Diseases (ND)</td>
</tr>
<tr>
<td>Parkinson</td>
</tr>
<tr>
<td>Alzheimer</td>
</tr>
<tr>
<td>Huntington</td>
</tr>
<tr>
<td>Mental Illness (MI)</td>
</tr>
<tr>
<td>Depression</td>
</tr>
<tr>
<td>Anxiety</td>
</tr>
<tr>
<td>Valley Fever (VF)</td>
</tr>
<tr>
<td>Valley Fever</td>
</tr>
<tr>
<td>Asthma</td>
</tr>
<tr>
<td>Asthma</td>
</tr>
<tr>
<td>Coronary Atherosclerosis</td>
</tr>
<tr>
<td>Coronary Atherosclerosis</td>
</tr>
<tr>
<td>Associated Diseases (ADs) with most frequent hospitalizations</td>
</tr>
<tr>
<td>Births</td>
</tr>
<tr>
<td>Respiratory System</td>
</tr>
<tr>
<td>Circulatory System</td>
</tr>
<tr>
<td>Digestive System</td>
</tr>
<tr>
<td>Genitourinary System</td>
</tr>
<tr>
<td>Encounter for antineoplastic chemotherapy</td>
</tr>
<tr>
<td>Unsuspected septicemia</td>
</tr>
<tr>
<td>Other chest pain</td>
</tr>
<tr>
<td>Dehydration</td>
</tr>
<tr>
<td>Cellulitis and abscess of leg</td>
</tr>
<tr>
<td>Osteoarthritis</td>
</tr>
<tr>
<td>Diabetes mellitus</td>
</tr>
<tr>
<td>Mental Disorders</td>
</tr>
<tr>
<td>Code Range</td>
</tr>
<tr>
<td>------------</td>
</tr>
<tr>
<td>1: 001-139</td>
</tr>
<tr>
<td>2: 140-239</td>
</tr>
<tr>
<td>3: 240-279</td>
</tr>
<tr>
<td>4: 280-289</td>
</tr>
<tr>
<td>5: 290-319</td>
</tr>
<tr>
<td>6: 320-389</td>
</tr>
<tr>
<td>7: 390-459</td>
</tr>
<tr>
<td>8: 460-519</td>
</tr>
<tr>
<td>9: 520-579</td>
</tr>
</tbody>
</table>

**Methodology**

**Data Sources**

**Hospital Admissions**

Five years of hospitalizations and aftercare services data were obtained from the Texas Hospital Inpatient Research Data files (RDF) from the Texas Department of State Health Services (TDSHS), Center for Health Statistics, Austin, Texas for years 2010 through 2014 for El Paso County, Texas –a total of 299,804 hospitalization registrations. The data included the following five variables: the date of admission, census block group of the patient, the patient’s age, gender, and the principal diagnostic code from the International Classification of Diseases, Ninth Revision (ICD)-9 (see Table 4.1). The principal diagnostic code was preferred over other diagnostic codes because it better captures the exacerbations of disease as opposed to other diagnostics due to existing diseases (CMS, 1990).
TDSHS Center for Health Statistics is responsible for the collection and release of hospital discharge data from all state licensed hospitals except hospitals located in a county with a population less than 35,000, or those located in a county with a population more than 35,000 and with fewer than 100 licensed hospital beds and not located in an area that is delineated as an urbanized area by the United States Bureau of the Census. Exempt hospitals also include hospitals that do not take insurance payment or government reimbursement. Each individual hospital is responsible for the accuracy and completeness of its data and it is validated through a process of automated auditing and verification (TDSHS, 2015). The hospitals at El Paso, TX that met these requirements for the period studies are: Las Palmas Medical Center; Del Sol Medical Center; Hospitals of Providence (Memorial Campus, Sierra Campus, and East Medical Center); and University Medical Center of El Paso. During the utilization review, hospitals may use InterQual Level of Care Criteria to assess the clinical appropriateness of patient services by a robust clinical detail to consider the severity of illness, comorbidities and complications (McKesson Corporation, 2013).

PM and Weather Data

Data for maxima of hourly average \( \text{PM}_{10} \) concentrations, maximum hourly average wind speed (m/h), maximum hourly and daily average temperature (°F), maximum hourly average and daily average relative humidity measured at a Continuous Air Monitoring Station (CAMS) number 12 (CAMS-12) at a site located near the University of Texas at El Paso (UTEP) in El Paso, Texas, from 2010-2014 were obtained from the website of the site operator, the Texas Commission on Environmental Quality (TCEQ). For days in which the UTEP CAMS-12 site was not operating, data were obtained from the TCEQ CAMS 41 at Chamizal in El Paso, approximately 2 miles southeast of the UTEP CAMS-12 station. We compared the different effects observed during a
dusty day period to non-dusty day periods during the cold (October–March) and hot (April–September) seasons. It was assumed that hospitalized people were having some activity outdoors or were somehow exposed to these DEs.

Maximum hourly PM_{10} concentrations and wind speeds were used because atmospheric dust levels in El Paso often display high short-term peaks (Lee et al., 2009) from dust events that average approximately 2 hours in length (Novlan et al., 2007) that lead to high acute exposures, and using the daily mean could underestimate these effects. These drastic changes in atmospheric particle concentration could exceed an order of magnitude increase over a few hours and differ under high and low wind speed conditions. High wind speed indicates the predominance of coarse particles and can be used as a surrogate variable for the PM_{10} in El Paso (Staniswalis et al., 2005). An increase from the previous day of an hourly average PM_{10} concentration of at least 100 micrograms per cubic meter, or 10 mph increase of maximum hourly average wind speed, were assumed to constitute a DE.

Because of the evidence of the prolonged health effects of a DE (Yu et al., 2012, & Meng, & Lu 2007) the day with PM_{10} increase >100µg/m^3 or the 10 mph increase in maximum hourly wind speed and the following 7 days were identified for analysis. We estimated the effects of the current day's DEs (lag 0) on all hospitalizations, and the effects of the DEs on the next day's admission (lag 1) and the following six days (lags 2–7) when available because of the frequency of DE in a week. These lag periods were selected to investigate the short-term effects of dust events on ND, MI, VF, ADs and ICD-9 categories hospitalizations.
**Socio-Economic and Demographic data**

In order to help us to identify susceptible individuals, economic characteristics, including income, and education for each patient address census block group were obtained from the U.S. Census Bureau's American Community Survey for the 2010-2014 period. This information was connected with the RDF’s Address Census Block Group code of each hospitalized patient in the county of El Paso, Texas. Population increase or decrease between 2010-2014 was obtained from census data in the county of El Paso, Texas, to remove these non-environmental confounding elements (population increase or decrease). In order to examine the modified effects of socio-economic factors, an average age, average income, and median education for each disease cohort were calculated.

**Statistical Analyses**

Relationships among dust exposures defined by meteorological parameters, hospital admissions and SES were investigated by using a quasi-Poisson regression model, the regression model with an overdispersed Poisson family. Statistical analyses were performed by data analysis with R and Python sequentially; statistical significance was determined by p<0.05.

**Aim 1)**

Investigate whether DE is associated with hospital admissions due to acute or accelerated disease progression of hospitalizations due to ND, MI, VF, Asthma, Coronary Atherosclerosis, AD, and all ICD-9 category diagnoses in the county of El Paso, TX over a five-year period from 2010-2014. It is hypothesized that the affected admissions in ND, MI, VF, Asthma, Coronary Atherosclerosis, AD, and ICD-9 category diagnoses will show positive association to DEs.
Model

A generalized linear model with quasi-Poisson or Poisson family was generated to determine the associations between DE and hospitalizations due to ND, MI, VF, Asthma, Coronary Atherosclerosis, AD, and ICD-9 category during eight-day period (the day of the dust exposure and week after the dust exposure, up to seven days) identified in El Paso, Texas. Cross-basis matrices for maximum PM$_{10}$, maximum wind speed, daily average of temperature, and daily average humidity were included in the regression model to account for the lagged effects of the predictors. Natural splines were used as smoothing function of time for any time-dependent outcome predictors or confounders with long-term trends and seasonal patterns not explicitly included in the model (Touloumi et al., 2004). Long-term trends and seasonal patterns (time with 7 degrees of freedom/year and day of the year) were analyzed with a natural cubic regression spline.

\[
\log E[Y_{\tau}] = \alpha + \beta_1 PM_{10,\tau+7} + \beta_2 WS_{\tau+7} + \gamma_1 Temp_{\tau+3} + \gamma_2 Humd_{\tau+5} + \gamma_3 s(time) + \gamma_4 s(day of year) + \gamma_5 DE + \gamma_6 DE_{7d} + \gamma_7 season + \gamma_8 holiday + \gamma_9 Weekday + \gamma_{10} Weekend + \gamma_{11} Population
\]

Where $E[Y_{\tau}]$ is the expected value of the Poisson distributed variable, $Y_{\tau}$, indicating the daily admissions count on a day $\tau$ for each diagnosis with $\text{Var}(Y_{\tau})$; $\alpha$ refers to the intercept of the hospital admissions; $\beta_i$ refers to the coefficients associated with the pollutant and windspeed ($i = 1, 2$); $\gamma_j$ the coefficients associated with other covariates ($j = 1, 2, \cdots, 11$); $PM_{10,\tau+7}$ is the cross-basis matrices of PM$_{10}$ maximum hourly level on day $\tau$ with lags up to seven days; $WS_{\tau+7}$ is the cross-basis matrices of wind speed maximum hourly average level on day $\tau$ with lags up to seven days; $Temp_{\tau+3}$ is the cross-basis matrices of average temperature by two lag strata, 0 and 1-3; $Humd_{\tau+5}$ is the cross-basis matrices of average humidity on day $\tau$ with lags up to five days; $DE$
is the maximum hourly average PM$_{10}$ of 150µg/m$^3$ and/or the maximum hourly average wind speed of 10 mph maximum hourly average on day $\tau$; $DE_{7_d}$ is DE plus the seven following days; season is the indicator variable for cold (October–March) and hot (April–September) period; indicator of a holiday; Weekday is the five working days from Monday to Friday; Weekend is Saturday and Sunday; Population is the estimated population increase of decrease; and $s(\cdot)$ denotes the smooth function of the variable. Several models were run for each outcome of interest, that is, ND, MI, VF, Asthma, Coronary Atherosclerosis, AD (independently and aggregated), and all ICD-9 categories.

This description is as a full model. Starting from this full model, the variable selection was performed, and the best model was selected for each disease. The best model differs depending on each disease. The stepwise variable selection technique was performed. Relative risk (RR) for each associated diagnosis was calculated (e.g., RR per 100µg/m$^3$ increase in PM$_{10}$ or 10mph increase in wind speed) based on the final selected regression model. The $\beta_1$ represents the log of expected counts of hospital admission per 100µg/m$^3$ unit change in PM$_{10}$, and $\beta_2$ represents the log of expected counts of hospital admission per 10mph increase in wind speed, which can be estimated from the Poisson regression analysis.

Aim 2)

Determine if demographic variables such as age and socio-economic status -indexed by income, and education level for each patient address CBG moderates the association between elevated PM$_{10}$ and wind speed exposure and hospitalizations. It is hypothesized that SES will moderate the association with overall hospital admissions due to elevated PM exposure and/or wind speed, with admissions being higher among individuals living in areas of lower SES and
lower education. In addition, it is hypothesized that age will mediate the association between overall hospital admissions and DEs.

**Model**

An association among DE and ND, MI, VF, Asthma, Coronary Atherosclerosis, AD, and all ICD-9 category and the modifying effect of the demographic factors (age, and SES -including income and education attainment by CBG) in the county of El Paso, Texas was looked upon. The demographic factors were added to the quasi-Poisson or Poisson regression model selected in Aim 1. SES data from the U.S. Census Bureau's American Community Survey for the 2010-2014 period was connected with the RDF’s Address CBG code of each hospitalized patient identified.

\[
\log E[Y_\tau] = \alpha + (\text{Selected variables in Aim 3}) + \ldots + \delta_1 \text{Age} + \delta_2 \text{Income} + \delta_3 \text{Education}
\]

Where \(E[Y_\tau]\) is the expected value of the Poisson distributed variable, \(Y_\tau\), indicating the daily admissions on a day \(\tau\) for each diagnosis; \(\alpha\) refers to the intercept of the hospital admissions; \(\delta_k\) refers to the coefficients of the demographic and SES variables \((k = 1, 2, 3)\); \(\text{Age}\) is average age of the CBG cohort; \(\text{Income}\) is average income of Hispanic in CBG; and \(\text{Education}\) refers to median education category in the CBG cohort. Separate analysis was conducted for each disease to determine the effect modification of PM\(_{10}\) and WS by adding the demographic and SES factors.

**Results**

During the study period, there were a total of 299,804 hospitalizations. The daily average admissions for AD were 73.30±29.76 with a minimum of 0 and a maximum of 320 hospitalizations. The greatest daily average admission was for Circulatory System diseases, with 17.17±7.03 with a minimum of 0 and a maximum of 68 hospitalizations. The fewest admissions
were for Valley fever, in an area where it is not very common, with only 44 hospital admissions from 2010-2014. The descriptive analysis of the dependent variables (diseases) is shown in Table 4.2.

Table 4.2 Descriptive analysis of disease categories and associated hospitalizations. El Paso, TX, 2010-2014. Categories in bold were found by the analyses to have some significant association with specified increases in PM$_{10}$ concentration and/or wind speed at some lag between 0 and 7. Categories in italic are part of AD.

<table>
<thead>
<tr>
<th>Diseases</th>
<th>Total</th>
<th>Min</th>
<th>Max</th>
<th>Average</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Valley Fever</td>
<td>44</td>
<td>0</td>
<td>1</td>
<td>0.02</td>
<td>0.15</td>
</tr>
<tr>
<td>ND</td>
<td>435</td>
<td>0</td>
<td>4</td>
<td>0.24</td>
<td>0.51</td>
</tr>
<tr>
<td>Coronary Atherosclerosis</td>
<td>2,974</td>
<td>0</td>
<td>16</td>
<td>1.63</td>
<td>1.60</td>
</tr>
<tr>
<td>Asthma</td>
<td>3030</td>
<td>0</td>
<td>18</td>
<td>1.66</td>
<td>1.59</td>
</tr>
<tr>
<td>MI</td>
<td>4107</td>
<td>0</td>
<td>14</td>
<td>2.25</td>
<td>1.73</td>
</tr>
<tr>
<td>Aftercare services (ICD-9 C.18)</td>
<td>8,258</td>
<td>0</td>
<td>28</td>
<td>4.52</td>
<td>3.21</td>
</tr>
<tr>
<td>Injury and poisoning (ICD-9 C.17)</td>
<td>21,398</td>
<td>0</td>
<td>63</td>
<td>11.72</td>
<td>4.89</td>
</tr>
<tr>
<td>Respiratory System (ICD-9 C.8)</td>
<td>23,401</td>
<td>0</td>
<td>96</td>
<td>12.82</td>
<td>8.93</td>
</tr>
<tr>
<td>Circulatory system (ICD-9 C.7)</td>
<td>31,345</td>
<td>0</td>
<td>68</td>
<td>17.17</td>
<td>7.03</td>
</tr>
<tr>
<td>AD</td>
<td>133,848</td>
<td>0</td>
<td>320</td>
<td>73.30</td>
<td>29.76</td>
</tr>
<tr>
<td>All ICD-9</td>
<td>299,804</td>
<td>0</td>
<td>632</td>
<td>61.51</td>
<td>164.19</td>
</tr>
<tr>
<td>Diabetes mellitus</td>
<td>1,069</td>
<td>0</td>
<td>6</td>
<td>0.59</td>
<td>0.81</td>
</tr>
<tr>
<td>Cellulitis and abscess of leg</td>
<td>2,128</td>
<td>0</td>
<td>7</td>
<td>1.17</td>
<td>1.15</td>
</tr>
<tr>
<td>Dehydration</td>
<td>2,254</td>
<td>0</td>
<td>11</td>
<td>1.23</td>
<td>1.29</td>
</tr>
<tr>
<td>Osteoarthrosis</td>
<td>3,324</td>
<td>0</td>
<td>12</td>
<td>1.82</td>
<td>2.15</td>
</tr>
<tr>
<td>Other chest pain</td>
<td>3,667</td>
<td>0</td>
<td>18</td>
<td>2.01</td>
<td>1.60</td>
</tr>
<tr>
<td>Unspecified septicemia</td>
<td>3,834</td>
<td>0</td>
<td>9</td>
<td>2.10</td>
<td>1.52</td>
</tr>
<tr>
<td>Mental Disorders</td>
<td>3,882</td>
<td>0</td>
<td>31</td>
<td>2.13</td>
<td>1.88</td>
</tr>
<tr>
<td>Encounter for antineoplastic chemotherapy</td>
<td>7,056</td>
<td>0</td>
<td>18</td>
<td>3.86</td>
<td>2.84</td>
</tr>
<tr>
<td>Genitourinary System</td>
<td>8,772</td>
<td>0</td>
<td>24</td>
<td>4.80</td>
<td>2.67</td>
</tr>
<tr>
<td>Digestive System</td>
<td>10,067</td>
<td>0</td>
<td>22</td>
<td>5.51</td>
<td>2.94</td>
</tr>
<tr>
<td>Circulatory System</td>
<td>12,361</td>
<td>0</td>
<td>34</td>
<td>6.77</td>
<td>3.37</td>
</tr>
<tr>
<td>Respiratory System</td>
<td>14,914</td>
<td>0</td>
<td>75</td>
<td>8.17</td>
<td>6.45</td>
</tr>
<tr>
<td>Births</td>
<td>60,520</td>
<td>0</td>
<td>192</td>
<td>33.14</td>
<td>17.13</td>
</tr>
</tbody>
</table>
The estimated average daily hourly maximum concentration of PM$_{10}$ was 94.14±178.11 μg/m$^3$ and the minimum and maximum values were 7.8 μg/m$^3$ and 4739.3 μg/m$^3$ respectively. The estimated maximum daily hourly average of wind speed was 12.38±5.01mph and the minimum and maximum values were 2.5 mph and 34.2 mph respectively. The average daily temperature was 67.24±15.46°F and the minimum and maximum values were 10.8 and 94.4°F respectively. The descriptive analysis of the independent variables (pollutants and temperature) is shown in Table 4.3.

Table 4. 3 Descriptive analysis of maximum Windspeed (mph), maximum PM$_{10}$, maximum and average Temperature (°F), maximum and average Relative Humidity (%). El Paso, TX, 2010-2014.

<table>
<thead>
<tr>
<th></th>
<th>Max Wind Speed</th>
<th>Max PM$_{10}$</th>
<th>Max Temp</th>
<th>Avg Temp</th>
<th>Max RH</th>
<th>Avg RH</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>2.5</td>
<td>7.8</td>
<td>14.8</td>
<td>10.8</td>
<td>8.7</td>
<td>4.40</td>
</tr>
<tr>
<td>Max</td>
<td>34.2</td>
<td>4739.3</td>
<td>105.9</td>
<td>94.4</td>
<td>100</td>
<td>89.3</td>
</tr>
<tr>
<td>Average</td>
<td>12.38</td>
<td>94.14</td>
<td>77.64</td>
<td>67.24</td>
<td>51.29</td>
<td>33.39</td>
</tr>
<tr>
<td>SD</td>
<td>5.01</td>
<td>178.11</td>
<td>15.68</td>
<td>15.46</td>
<td>20.87</td>
<td>16.14</td>
</tr>
</tbody>
</table>

Summary of Significant Associations

The Relative Risk (RR) results indicate that DE increases the risk of patient admission due to Neurodegenerative diseases during the 7th day after DE (RR of 1.051: 1.009–1.095 per 100 μg/m$^3$ increase of max PM$_{10}$); AD (RR of 1.005: 1.001–1.009 for day 0; RR of 1.004: 1.001–1.007 and RR of 1.003: 1.001–1.005 for day 1 and 2 after DE per 100 μg/m$^3$ increase of max PM$_{10}$, respectively); antineoplastic chemotherapy and rehabilitation procedure during the 7th day after DE (RR of 1.023: 1.005–1.040 per 100 μg/m$^3$ increase of max PM$_{10}$); Genitourinary Diseases during the day of DE (RR of 1.056: 1.001–1.114 per 10 mph increase of max wind speed); Valley Fever hospitalizations during the 6th day after a DE (Relative risk of 1.468: 1.014–2.126 per 10 mph increase of max wind speed); Coronary Atherosclerosis hospitalizations during the day of DE
(RR of 1.136: 1.063–1.214 per 10 mph increase of max wind speed); Respiratory system hospitalizations during the 6th day after a DE and after age and medium education was added to the model (RR of 1.007: 1.001–1.014 per 100 μg/m³ increase of PM₁₀). Borderline significance was found for births hospitalizations during the 3rd day after DE (RR of 1.005: 1.0002–1.010 per 100 μg/m³ increase of PM₁₀); Septicemia during the day of DE (RR of 1.019: 1.00005–1.039 per 100 μg/m³ increase of PM₁₀); all ICD-9 Category hospitalizations during the day of DE (RR of 1.005: 1.0002–1.009 per 100 μg/m³ increase of PM₁₀) (Table 4.4).

The significant Poisson regression results, that is the analysis with the maximum PM₁₀ concentration and maximum wind speed adjusted by the significance of meteorological variables, estimated population increase or decrease, seasonality, holiday and weekday between the diseases are shown in Table 4.4 with their respective lag day (LD) relative risk (RR) and 95% confidence interval (CI). The hospitalizations for ND (LD 7), AD (LD 0-2), Chemotherapy (LD 7), and respiratory diseases (LD 6) were positively correlated (p-values<0.05) with maximum PM₁₀, and weekday (p<0.01); The hospitalizations due to Chemotherapy AD and Respiratory diseases decreased in the cold season and holiday compared to hot season and non-holiday (p<0.01). The hospitalizations for births (LD 3) and septicemia (LD 0) were positively correlated (p-values<0.05) with maximum PM₁₀, and weekday (p<0.01). The hospitalizations due to births decreased in the holiday compared to non-holiday (p<0.01). The hospitalizations for all ICD-9 diseases (LD 0) were positively correlated (p-values<0.05) with maximum PM₁₀, and weekday (p<0.01). The hospitalizations due to all ICD-9 decreased in the holiday compared to non-holiday (p<0.01).

The hospitalizations for Genitourinary Diseases (LD 0), Valley Fever (LD 6) and Coronary Atherosclerosis (LD 0), were positively correlated (p<0.05) with maximum wind speed and weekday (p<0.01) with exception of Valley Fever; The hospital admission due to Coronary
Atherosclerosis decreased on holidays compared to non-holidays (p<0.01). In the case of ICD-9 category hospitalizations, circulatory system diseases (LD 0 and 7), aftercare services, injury and poisoning were positively correlated on LD 7 (p<0.05) with maximum PM$_{10}$, and weekday (p<0.01); and decreased in the cold season and holiday compared to hot season and non-holiday (p<0.01). Injury and poisoning were positively correlated (p<0.05) with maximum wind speed on LD 0 and increased on weekday compared to weekend (p<0.01) and decreased in the cold season and holiday compared to hot season and non-holiday (p<0.01).

Table 4.4 Significant associations between the diseases and DE-related variables, and the corresponding relative risk with 100-unit increase in maximum PM$_{10}$ and 10-unit increase in maximum WS, El Paso, TX, 2010-2014.

<table>
<thead>
<tr>
<th>Data</th>
<th>Variable</th>
<th>Diseases</th>
<th>Lag day</th>
<th>Higher risk</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>RR</td>
</tr>
<tr>
<td>Diseases with high hospitalization frequency</td>
<td>ND</td>
<td>7</td>
<td>1.051</td>
<td>1.009</td>
</tr>
<tr>
<td>PM$_{10}$</td>
<td>AD</td>
<td>0</td>
<td>1.005</td>
<td>1.001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1</td>
<td>1.004</td>
<td>1.001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>1.003</td>
<td>1.001</td>
</tr>
<tr>
<td></td>
<td>Chemotherapy</td>
<td>7</td>
<td>1.023</td>
<td>1.005</td>
</tr>
<tr>
<td></td>
<td>Births</td>
<td>3</td>
<td>1.005</td>
<td>1.00006</td>
</tr>
<tr>
<td></td>
<td>Septicemia</td>
<td>0</td>
<td>1.019</td>
<td>1.00005</td>
</tr>
<tr>
<td>WS</td>
<td>Genitourinary</td>
<td>0</td>
<td>1.056</td>
<td>1.001</td>
</tr>
<tr>
<td></td>
<td>Valley Fever</td>
<td>6</td>
<td>1.468</td>
<td>1.014</td>
</tr>
<tr>
<td></td>
<td>Coronary Atherosclerosis</td>
<td>0</td>
<td>1.117</td>
<td>1.025</td>
</tr>
<tr>
<td>ICD9 Category</td>
<td>PM$_{10}$</td>
<td>Circulatory system</td>
<td>0, 7</td>
<td>1.011</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Aftercare services</td>
<td>7</td>
<td>1.018</td>
</tr>
<tr>
<td></td>
<td></td>
<td>All ICD-9</td>
<td>0</td>
<td>1.005</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Injury and poisoning</td>
<td>7</td>
<td>1.011</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Respiratory system</td>
<td>6</td>
<td>1.007</td>
</tr>
<tr>
<td></td>
<td>WS</td>
<td>Injury and poisoning</td>
<td>0</td>
<td>1.037</td>
</tr>
</tbody>
</table>
Age, Income and Education Associations with Hospitalizations

There is a significant correlation ($p<0.05$) between chemotherapy, AD, births, circulatory system diseases, injury and poisoning, after-care service, respiratory system diseases and all ICD-9 categories and patients’ admission to the hospital due to age and SES factors. Chemotherapy hospitalizations were weakly correlated ($p=0.056$) with average income. AD hospitalizations were negatively correlated with age ($p<0.01$). Births hospitalizations were negatively correlated with median education ($p<0.01$) and positively correlated with age ($p<0.01$). In the case of ICD-9 groups, circulatory system diseases, injury and poisoning, aftercare services, and respiratory system diseases decreased as median education increases ($p<0.01$). Aftercare services and Injury and poisoning were positively correlated with average income ($p<0.01$). All ICD-9 categories and respiratory system hospitalizations were negatively correlated with age ($p<0.01$) (Table 4.5).
Table 4.5 Quasi-Poisson regression matrix of significant relationships between diseases and age and SES factors at El Paso, TX, 2010-2014.

<table>
<thead>
<tr>
<th>Data</th>
<th>Hospitalizations</th>
<th>Coef. after SES factors are added</th>
<th>Estimate</th>
<th>Std. Error</th>
<th>t value</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Estimate</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Diseases with high hospitalization frequency</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Chemotherapy</td>
<td>Average Income</td>
<td>1.75E-06</td>
<td>0.000</td>
<td>1.909</td>
<td>0.056</td>
</tr>
<tr>
<td></td>
<td></td>
<td>AD</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Births</td>
<td>Age</td>
<td>-0.005</td>
<td>0.001</td>
<td>-7.175</td>
<td>0.000*</td>
</tr>
<tr>
<td></td>
<td>ICD9 Category</td>
<td>Med. Education</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Circulatory system</td>
<td>Medium Education</td>
<td>-0.020</td>
<td>0.006</td>
<td>-3.350</td>
<td>0.001*</td>
</tr>
<tr>
<td></td>
<td>Injury and poisoning</td>
<td>Ave. Income &amp;</td>
<td>4.26E-06</td>
<td>0.000</td>
<td>4.058</td>
<td>0.000*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Med. Education</td>
<td>-0.029</td>
<td>0.006</td>
<td>-4.909</td>
<td>0.000*</td>
</tr>
<tr>
<td></td>
<td>Aftercare services</td>
<td>Ave. Income &amp;</td>
<td>2.15E-06</td>
<td>0.000</td>
<td>2.327</td>
<td>0.020*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Med. Education</td>
<td>-0.023</td>
<td>0.006</td>
<td>-3.600</td>
<td>0.000*</td>
</tr>
<tr>
<td></td>
<td>Respiratory system</td>
<td>Age &amp;</td>
<td>-0.002</td>
<td>0.001</td>
<td>-3.113</td>
<td>0.002*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Med. Education</td>
<td>-0.013</td>
<td>0.006</td>
<td>-2.075</td>
<td>0.038*</td>
</tr>
<tr>
<td></td>
<td>All ICD-9</td>
<td>Age</td>
<td>-0.006</td>
<td>0.001</td>
<td>-8.547</td>
<td>0.000*</td>
</tr>
</tbody>
</table>

*Statistically significant at p-value ≤ 0.05.

Table 4.6 shows that the relative risk of chemotherapy encounters lowers after the average income effect is analyzed from 1.023 to 1.020 on LD 7 (95% CI= [1.005–1.036] per 100 μg/m³ increase of max PM_{10}). The RR of AD hospitalizations lowers after the age effect is analyzed from 1.005 to 1.001 on LD 0 (95% CI= [1.001–1.009] per 100 μg/m³ increase of max PM_{10}). The RR of births hospitalizations stays the same after the age and median education effect is analyzed 1.005 on LD 2 and 3 (95% CI= [1.0002–1.010] per 100 μg/m³ increase of max PM_{10}). The RR of circulatory system hospitalizations lowers after the median
education effect is analyzed from 1.011 to 1.010 on LD 7 (95% CI= [1.003–1.017] per 100 μg/m³ increase of max PM₁₀). The RR of injury and poisoning and aftercare services lowers after the average income and median education effect is analyzed from 1.011 to 1.009 on LD 7 (95% CI= [1.001–1.017] per 100 μg/m³ increase of max PM₁₀), and from 1.018 to 1.017 on LD 7 (95% CI= [1.003–1.032] per 100 μg/m³ increase of max PM₁₀), respectively (Table 4.6). The RR of respiratory system hospitalizations increases after age and median education effect is analyzed from 1.006 to 1.007 on LD 6 (95% CI= [1.001–1.014] per 100 μg/m³ increase of max PM₁₀). The RR of all ICD-9 category hospitalizations decreases after age effect is analyzed from 1.005 to 1.000 on LD 0 (95% CI= [0.998–1.003] per 100 μg/m³ increase of max PM₁₀) and increases after age effect is analyzed from 1.002 to 1.003 on LD 1 and 2 (95% CI= [1.001–1.004] per 100 μg/m³ increase of max PM₁₀) (see Figure 4.11).
Table 4. Comparison of the Relative Risk estimates and 95% confidence intervals before and after the age, income and education are analyzed in the RR estimates. El Paso, TX, 2010-2014.

<table>
<thead>
<tr>
<th>Data</th>
<th>Hospitalizations RR after SES factors are added</th>
<th>Lag day</th>
<th>Hospitalizations RR after SES factors are added</th>
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<td>Diseases with high</td>
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<td>hospitalization frequency</td>
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<tr>
<td>Chemotherapy</td>
<td>7</td>
<td>1.023</td>
<td>1.005</td>
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<tr>
<td>Average Income</td>
<td></td>
<td>1.020</td>
<td>1.005</td>
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<tr>
<td>AD</td>
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<td>1.005</td>
<td>1.001</td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td>1.001</td>
<td>0.997</td>
</tr>
<tr>
<td>Births</td>
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<td>1.0006</td>
</tr>
<tr>
<td>Age &amp; Med. Education</td>
<td>2</td>
<td>1.005</td>
<td>1.0002</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>1.005</td>
<td>1.0002</td>
</tr>
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<td>Circulatory system</td>
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<td>1.011</td>
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<td></td>
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<td>1.009</td>
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<td>1.0002</td>
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<td>Aftercare services</td>
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<tr>
<td>Ave. Income &amp; Med. Education</td>
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<td>1.017</td>
<td>1.003</td>
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<td>6</td>
<td>1.007</td>
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</tr>
<tr>
<td>Age &amp; Med. Education</td>
<td></td>
<td>1.0065</td>
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<tr>
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</tr>
<tr>
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<td>1.001</td>
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</tr>
<tr>
<td></td>
<td>2</td>
<td>1.003</td>
<td>1.001</td>
</tr>
</tbody>
</table>

**Lag-Response Bar Graphs of the Relative Risk for DE and Diseases**

The Relative Risk compares the risk of a DE, expressed by maximum hourly PM$_{10}$ increment of 100 µg/m$^3$ and/or maximum hourly average wind speed increment of 10 mph, in seven days including the day of the DE and six days thereafter.

There is an association between maximum PM$_{10}$ and patient’s admission due to neurodegenerative diseases after a 100-unit increase in maximum PM$_{10}$. Results indicate that the
risk of ND increases 7 days after exposure to high levels of PM$_{10}$ (Relative risk [RR] of 1.051: 95% CI= [1.009–1.095] per 100 μg/m$^3$ increase of max PM$_{10}$) (Figure 4.1). Demographic factors were not significantly associated.

![Lag-response a 100-unit increase in max PM10](image)

**Figure 4.1 Risk Ratio of ND per Change of Maximum PM$_{10}$.

There is an association between PM$_{10}$ and patient’s admission due to other Associated Diseases (Table 4.1) after a 100-unit increase in maximum PM$_{10}$. Results indicate that exposure to high levels of PM$_{10}$ increases the risk of AD (RR of 1.005: 95% CI= [1.001–1.009] for day 0; RR of 1.004: 95% CI= [1.001–1.007] for day 1 after a DE; RR of 1.003: 95% CI= [1.001–1.005] for day 2 after a DE per 100 μg/m$^3$ increase of max PM$_{10}$) (Figure 4.2).
There is an association between maximum PM$_{10}$ and patient admission due to antineoplastic chemotherapy and rehabilitation procedure after a 100-unit increase in maximum PM$_{10}$. Results indicate that the risk of antineoplastic chemotherapy and rehabilitation procedure increases 7 days after exposure to high levels of PM$_{10}$ (RR of 1.023; 95% CI= [1.005–1.040] per 100 μg/m$^3$ increase of max PM$_{10}$) (Figure 4.3).
There is an association between maximum wind speed and patient admission due to Genitourinary System disease after a 10-unit increase in maximum hourly wind speed. Results indicate that the risk of Genitourinary System diseases increases the day of exposure (LD 0) to high levels of maximum hourly wind speed (RR of 1.056: 95% CI= [1.001–1.114] per 10 mph increase of max wind speed) (Figure 4.4). Demographic factors were not significantly associated.

![Figure 4.4 Risk Ratio of Genitourinary System diseases per Change of Maximum PM$_{10}$](image)

There is an association between maximum wind speed and patient’s admission due to Valley Fever after a 10-unit increase in maximum wind speed. Results indicate that exposure to higher levels of wind speed increases the risk of Valley Fever hospitalizations (RR of 1.468: 95% CI= [1.014–2.126] per 10 mph increase of max wind speed) for the day 6th after a DE (Figure 4.5).
Figure 4. 5 Risk Ratio of Valley Fever per Change of Maximum Windspeed. Demographic factors were not significantly associated.

There is an association between maximum wind speed and patient’s admission due to coronary atherosclerosis after a 10-unit increase in maximum wind speed. Results indicate that exposure to high levels of wind speed increases the risk of coronary atherosclerosis hospitalizations on LD 0, the day of exposure (RR of 1.136: 95% CI= [1.063–1.214] per 10 mph increase of max wind speed) and the relative risk significantly lowers after day 6th of DE to 0.949 (95% CI= [0.904-0.997] per 10 mph increase of max wind speed) (Figure 4.6). Demographic factors were not significantly associated.
There is an association between maximum PM$_{10}$ and patient’s admission due to circulatory system diseases (ICD-9 Category 7) after a 100-unit increase in maximum PM$_{10}$. Results indicate that the risk of circulatory system diseases increases at lag day 0 (it is borderline significant) (RR of 1.009; 95% Cl= [1.0004–1.017] per 100 μg/m$^3$ increase of max PM$_{10}$) and 7 days after exposure to high levels of PM$_{10}$ (RR of 1.011; 95% Cl= [1.003–1.018] per 100 μg/m$^3$ increase of max PM$_{10}$) (Figure 4.7).

Figure 4. 6 Risk Ratio of Coronary Atherosclerosis diseases per Change of Maximum Wind speed.
Figure 4. 7 (A) Risk Ratio of Circulatory system diseases (ICD-9 Category 7) per Change of Maximum PM$_{10}$ and (B) after medium education was analyzed. Income was not significant (p=0.41).

There is an association between maximum PM$_{10}$ and patient’s admission due to injury and poisoning (ICD-9 Category 17) after a 100-unit increase in maximum PM$_{10}$. Results indicate that the risk of injury and poisoning increases 7 days after exposure to high levels of PM$_{10}$ (RR of 1.011: 95% CI= [1.002–1.019] per 100 μg/m$^3$ increase of max PM$_{10}$) (Figure 4.8).

Figure 4. 8 (A)Risk Ratio of Injury and poisoning (ICD-9 Category 17) per Change of Maximum PM$_{10}$ and (B) after income and medium education was analyzed.

There is an association between maximum PM$_{10}$ and patient’s admission due to after care services or therapies (ICD-9 Category 18) after a 100-unit increase in maximum PM$_{10}$. Results
indicate that the risk of after care services or therapies increases 7 days after exposure to high levels of PM$_{10}$ (RR of 1.018: 95% CI= [1.001–1.034] per 100 μg/m$^3$ increase of max PM$_{10}$) (Figure 4.9).

Figure 4.9(A)Risk Ratio of Aftercare services or therapies (ICD-9 Category 18) per Change of Maximum PM$_{10}$ and (B) after income and medium education was analyzed.

There is an association between maximum PM$_{10}$ and patient’s admission due to respiratory system diseases (ICD-9 Category 8) after a 100-unit increase in maximum PM$_{10}$. After age and medium education was added to the model, results indicate that the risk of diseases of the respiratory system (ICD-9 Category 8) increases 6 days after exposure to high levels of PM$_{10}$ (RR of 1.007: 1.001–1.014 per 100 μg/m$^3$ increase of PM$_{10}$). Without demographic factors it was not significant (see Figure 4.10).
Figure 4. 10 (A) Risk Ratio of respiratory system diseases (ICD-9 Category 18) per Change of Maximum PM$_{10}$ and (B) after age and medium education was analyzed.

There is an association between maximum PM$_{10}$ and patient’s admission due to All ICD-9 Category admissions after a 100-unit increase in maximum PM$_{10}$. Results indicate that there is a borderline significant risk of all ICD-9 Category admissions increase at day 0 after exposure to high levels of PM$_{10}$ (RR of 1.005: 1.0002–1.009 per 100 μg/m$^3$ increase of PM$_{10}$) (Figure 4.11).

Figure 4. 11 (A) Risk Ratio of All ICD-9 Category admissions per Change of Maximum PM$_{10}$ and (B) after age was analyzed.
There is an association between maximum PM$_{10}$ and patient’s admission due to births after a 100-unit increase in maximum PM$_{10}$. Results indicate that there is a borderline significant risk of births admissions increase at day 3 after exposure to high levels of PM$_{10}$ (RR of 1.005: 1.0002–1.010 per 100 μg/m$^3$ increase of PM$_{10}$) (Figure 4.12).

Figure 4. 12 (A) Risk Ratio of births admissions per Change of Maximum PM$_{10}$ and (B) after age and medium education was analyzed.

There is an association between maximum PM$_{10}$ and patient’s admission due to Septicemia after a 100-unit increase in maximum PM$_{10}$. Results indicate that there is a borderline significant risk of Septicemia admissions increase at day 0 after exposure to high levels of PM$_{10}$ (RR of 1.019: 1.00005–1.039 per 100 μg/m$^3$ increase of PM$_{10}$) (Figure 4.13). Demographic factors were not significantly associated.
Discussion

**Maximum hourly PM$_{10}$ Associations**

Results indicate that exposure to maximum hourly PM$_{10}$ with increments of 100 $\mu$g/m$^3$ increases the risk of patient admission due to ND (LD 7), AD (LD 0-2), circulatory system (LD 7), injury and poisoning (LD 7), encounter for antineoplastic chemotherapy (LD 7), aftercare services (LD 7) and respiratory system (LD 6). There is a borderline significant risk of patient admission due to births (LD 3), septicemia (LD 0), and all ICD-9 category (LD 0) hospitalizations. Encounters for antineoplastic chemotherapy and aftercare services are based on prior appointments and it could mean that people prefer to delay their hospital visit by one week because of a dusty day. ND, circulatory system diseases, and injury and poisoning hospitalizations significantly increases with PM$_{10}$ increments of 100 $\mu$g/m$^3$ on the 7th day and a borderline significance on day 0 for circulatory system diseases. These diseases have a common RR graphs pattern, a non-significant increase of hospitalization on the day of DE and then the curve lowers non-significantly and significantly increases again on day 7. This could be because the data on day 0 was not enough.
to be significant but still shows an increase of hospitalizations. The significant increase of hospitalizations in day 7 could be that it takes six days after a DE to develop health problems in the patient system and the symptoms appear at a level requiring hospitalization on day 7 after a DE. During a DE the atmosphere contains resuspensions of toxic deposited metals previously emitted from several point sources at El Paso (Staniswalis et al., 2005 & Van Pelt et al., 2020) that could be affecting patients with ND. Lee and Kim (2016) reported a significant increase in emergency admission risk for Parkinson’s disease at lag5, lag6, and lag7 (OR at lag7: 1.043, [95% CI: 1.005, 1.083] with 10 µg/m³ increase in PM$_{10}$ in Seoul, Korea. Both results indicate a short-term exposure to PM$_{10}$ may contribute to the risk of ND disease aggravation through neuroinflammation.

In this study, a significant increase in hospitalization risk for circulatory system diseases with 100 unit increase maximum hourly PM$_{10}$ was found on lag day 0 and a delay of 7 days, with a borderline significance on day 0 (lower 95% CI=1.0004). These results are similar with Anyang et al. (2017) who states that the strongest effects of PM$_{10}$ to ischemic heart disease is at lag day 0 and lag day 7.

Lag effects of particulate matter on human health could be explained by the fact that it takes time for a human body to accumulate pollutants during a short-term exposure which contributes to a prolonged inflammation that may trigger a disease process (Santos et al., 2008). Inflammation is the first line of defense against toxins, infections and injuries in the body. When inflammatory cells remain for a prolonged time in blood vessels, they promote the buildup of hazardous plaque, the arteries may thicken and trigger a heart attack or stroke. Signs of acute inflammation can appear within hours or days, depending on the cause and in some cases, they can rapidly become severe. How it develops and how long it will last depend on the cause, which part
of the body is affected and individual factors (e.g., obesity, smoking, respiratory problems, and unhealthy diet) (Healthline Media, 2021). Also, different kinds of diseases in different locations may have clinical manifestations with different severity, affecting the time lag of medical attendance (Zhang et al., 2021).

In the case of AD, the association was significant on lags of 0-2 days. This is because an aggregated effect of all the frequent causes of hospitalizations (5% or more of all hospitalizations) during a DE that show that DE triggers a hospitalization during the day 0 and/or the following two days, and the effect gradually diminishes and slightly increases on the 7th day. Some of those AD diseases (Births, Respiratory system, Asthma, Digestive System, Septicemia, Other Chest Pain, Dehydration, Cellulitis and Abscess of leg, Osteoarthritis, Diabetes Mellitus and Mental Disorders) might not have a positive but not significant association by themselves (probably because there are too few cases in a day) but joined together they show a significant association with DE during the day 0 and the following two days (Figure 4.2). In addition, all ICD-9 Category admissions increase at day 0. This is because an aggregated effect of all the causes of hospitalizations during a DE that show that DE triggers a hospitalization during the day 0.

**Sub-Analysis**

A separate analysis was made of DE association with days in which the National Weather Service reported blowing dust (BLDU) at El Paso Airport in addition to days with PM10 levels >150 μg/m³, and wind speed > 10mph. Births were significantly associated with exposure to BLDU, increasing the risk of births on the 3rd day after a DE (RR of 1.006: 1.001–1.011 per 100 μg/m³ increase of PM10). In this analysis, births were borderline significantly associated with a 100-unit increase in maximum PM10 at day 3 after a DE (RR of 1.005: 1.0002–1.010 per 100 μg/m³ increase of PM10) (Figure 4.12).
Maximum Wind Speed Associations

Results indicate that exposure to maximum hourly average wind speed with increments of 10mph increases the risk of patient’s admission due to Genitourinary System diseases (LD 0); Valley fever (LD 6); coronary atherosclerosis (LD 0); and injury and poisoning (LD 0). As high wind speed indicates the predominance of coarse particles irrespective of the presence of desert dust (but including local fugitive dust) and can be used as a surrogate variable for the PM$_{10}$ in El Paso (Staniswalis et al., 2005), patients were exposed to higher doses of coarse particulate matter and symptoms appeared on the day of the wind exposure. It could be that regardless of PM$_{10}$ source and concentration, increased wind lifts up some amount of dust from the surface and kicks up heavy metals, microbes and other toxics on it and people are more exposed to it. Genitourinary System as renal system vascularization is vulnerable to toxins lifted up during a dust exposure (Yang, et al., 2017). In the case of Valley Fever, it is known that symptoms may appear in a minimum of 7-10 days (CDC, 2021). This study at El Paso, TX shows that VF cases appear earlier on the 6th day after DE, which may be an indication that people in this area show a prompt development of symptoms affecting the time lag of medical attendance.

Results show a significant association with maximum hourly wind speed and hospitalizations due to coronary atherosclerosis at lag day 0 (RR of 1.136: 95% CI= [1.063–1.214] per 10 mph increase of max wind speed). Fasola et. al. (2021) found similar results for particulate matter in Pisa and Cascina, Tuscany, Italy, with the strongest effects of PM$_{10}$ due to cardiovascular hospitalizations immediately at lag 0 (odds ratio (OR) = 1.137, 95% CI= [1.023–1.264]) from 2011–2015. Takagi et al. (2020) performed a meta-analysis of multiple studies which found a significant correlation between increased wind speed and coronary artery disease, and suggested some possibilities that could explain their findings.
Weekend, Season and Holiday Associations

Hospitalizations due to ND (LD 7), AD (LD 0-2), all ICD-9 categories (LD 0), Circulatory System Disease (LD 0, 7), Respiratory System Disease (LD 6), Births (LD 3), Septicemia (LD 0), Aftercare Services (LD 7), Chemotherapy (LD 7) (associated to 100 $\mu$g/m$^3$ increase of PM$_{10}$), Genitourinary Disease, Coronary Atherosclerosis (associated to 10 mph increase of max wind speed on LD 0), and injury and poisoning (associated to both increases of wind speed and PM$_{10}$ on LD 0, 7) increased on weekday as compared to weekend ($p<0.01$). This could be because patients prefer to go to the hospital in El Paso during a weekday more so than during a weekend and because most of the appointments for Aftercare Services and Chemotherapy are during the week.

Hospitalizations due to Chemotherapy (LD 7), Circulatory System Disease (LD 0, 7), Births (LD 3), Aftercare Services (LD 7), all ICD-9 categories (LD 0), and AD (LD 0-2) (associated to 100 $\mu$g/m$^3$ increase of PM$_{10}$), Coronary Atherosclerosis (associated to 10 mph increase of max wind speed on LD 0), and injury and poisoning (associated to both increases of wind speed and PM$_{10}$ on LD 0, 7) decreased in the cold season and holiday compared to in hot season and non-holiday ($p<0.01$). Thus, indicating that there is an increase of hospitalizations during the hot season and non-holiday. Dust events in the hot season may increase these hospitalizations. In addition, people in El Paso may avoid going to the hospital during a holiday.

Demographic Associations

By adding the demographic variables (age, and socio-economic status indexed by income, and education level) into the RR analysis, a significantly modified effect (moderate/mediate) was found between DE and chemotherapy encounters (LD 7), AD (LD 0-2), births (LD 3), circulatory system diseases (LD 0, 7), aftercare services (LD 7), respiratory system diseases (LD 6), all ICD-9 categories (LD 0) (associated to 100 $\mu$g/m$^3$ increase of PM$_{10}$), and injury and poisoning
(associated to both increases of wind speed and PM$_{10}$ on LD 0, 7) at El Paso County, Texas. Results indicate a discrepancy in medical access in these patients with medium and low SES. Patients with higher income may have more financial/insurance access than patients with medium or low income.

The results indicate that as average income increases, the chances of a patient being hospitalized due to chemotherapy encounters increases ($p=0.056$) and the diminishing of the RR on lag day 7 indicates that there is a need in patients to pay for their chemotherapy services. As their income increases, so increases their availability to pay for their services. Even though it is a weak association, it is still significant because the p value is less than 0.1. Paying for cancer treatment can be a financial burden and its costs are rising. It may be due to out-of-pocket costs for various cancer treatments, including treatments some insurance plans do not cover. Therefore, the results may indicate a need of cost-effective payment models (Newcomer et al., 2014).

As age decreases, the chances of a patient being hospitalized due to AD and all ICD-9 categories increases. This could be because there are more hospitalizations for births than any other category. Births are at age 0 and all other diseases in the AD category are a younger than an older population. The diminishing of the RR reaffirms the negative effect of age and hospitalization due to AD on the day of DE-Lag day 0. This could be explained considering that during a dust event, younger patients may take a day or more in developing a reaction due to high levels of DE and postpone their visit (Table 4.6 and Figure 4.2).

As median education decreases, the chances of a patient being hospitalized due to circulatory system diseases, births, and respiratory system diseases increases. The diminishing of the RR on lag day 0 and 7 reaffirms the negative effect of medium education and hospitalization due to circulatory system diseases, births, and respiratory system diseases. Patients with these
types of hospitalizations may have lower education and are more likely to have lower income and as a result, lower access to healthcare to pay for their hospitalization. It could also mean that patients with medium education have not cultivated healthy habits except for births.

As average income increases, the chances of a patient being hospitalized due to injury and poisoning, and aftercare services increases. As medium education decreases, the chances of a patient being hospitalized due to poisoning, and aftercare services increases. The diminishing of the RR on lag day 7 reaffirms the negative effect of average income and hospitalization due to injury and poisoning and aftercare services. Due to injury and poisoning and aftercare services, most patients may have lower education and are more likely to have lower income and therefore lower access to healthcare to pay for their hospitalization. Patients with higher income are more likely to go to the hospital than patients with lower income. It is known that high-SES individuals accumulate the most benefit from their knowledge, education, efficacy, and resources in adopting advanced health-related behaviors and using new medical technologies (Pampel et al., 2010).

Limitations

Limitations of the dataset used included that only the principal diagnosis was obtained, which does not indicate pre-existing conditions/comorbidities of the patient. Another limitation is that persons experiencing symptoms consistent with neurodegenerative or mental conditions, especially anxiety and depression, often have their disorder go unrecognized, because they do not explain their psychological symptoms explicitly, and because they commonly consult their primary physician and/or mental health provider instead of going to the hospital (Bushnell et al., 2005 and Tylee & Walters, 2007). In addition, 50% of people with depression never consult a health care provider, 95% never enter to secondary mental health services, and many more are
unrecognized and untreated (NCCMH, 2011). Even considering these limitations which suggest the hospital admission data may only represent a small proportion of cases, we were able to identify a pattern of association between neurodegenerative diseases and dust exposure but not for mental illness.

The limitation of considering the maximum hourly PM$_{10}$ average value during the day can underestimate the effect of daily hospitalizations, because the daily maximum value describes acute exposures but does not explain chronic exposures/ lower-intensity dust exposures happening over long periods of time: additional research should be pursued exploring the effects of longer-term exposures to dust and PM in El Paso.

There also is a difference between emergency room (ER) visits and hospital admissions (HA). These differences may affect the results and interpretation of observed air pollution-health associations. For example, HA are less frequent than ER visits; HA may represent more severe events than ER; and ER may be used for primary care by patients with low income (Winquist et al., 2012). Additional research should be pursued exploring the effects of PM, wind, and/or dust exposures in El Paso on ER visits.

Valley fever has a small incidence of 44 cases during the study period. Due to the small occurrence, we might have inaccurate estimation of the association of increased PM and wind with Valley fever.

Conclusions and Future Work

Hospitalizations due to Valley fever, Coronary Atherosclerosis, Genitourinary Diseases, Neurodegenerative Diseases, Injury and Poisoning, Chemotherapy, Septicemia, Aftercare services, Circulatory System Diseases, Injury and Poisoning, Respiratory System Diseases,
Associated Diseases, Births, and all ICD-9 categories were significantly positively associated with DE in El Paso, Texas between 2010 and 2014, at different lag periods after exposure, indicated from higher to lower risk. Valley fever has the highest hospitalization risk (RR of 1.468), and it is known to have a direct relationship with *Coccidioides* fungus in the soil and exposure during blowing dust days (Tong et al., 2017), although its incidence was small. The second highest association is with Coronary Atherosclerosis followed by Genitourinary Diseases and Neurodegenerative Diseases. AD diseases, representing in aggregate the most common causes of hospital admission in El Paso (Births, Respiratory System Diseases, Asthma, Circulatory System Diseases, Digestive System Diseases, Genitourinary Diseases, Chemotherapy, Septicemia, Other Chest Pain, Dehydration, Cellulitis and Abscess of leg, Osteoarthritis, Diabetes Mellitus and Mental Disorders) and all ICD-9 categories showed the lowest RR (1.005), and it could be due to a subtle effect that shows up as a result of the hospitalization aggregation but not for individual diagnoses, but it is still significant and demonstrates association with dust exposure at multiple lag days.

With these results it is important to inform the El Paso community of the increased hospitalization risk due to many causes including Valley fever, Coronary Atherosclerosis, Genitourinary Diseases, Neurodegenerative Diseases, Injury and Poisoning, Chemotherapy, Septicemia, Aftercare services, Circulatory System Diseases, Injury and Poisoning, Respiratory System Diseases, Associated Diseases, Births, and all ICD-9 categories during and in the week after a dust exposure day with 100μg/m³ increase in PM₁₀ or 10mph increase in wind speed. Health care providers should be informed of the need in patients with medium and low SES to pay for their chemotherapy services; circulatory system; aftercare services; injury and poisoning; births; and respiratory system during a dust exposure.
These findings have important implications because about 92% of the world’s population resides in areas where particulate matter concentrations are greater than the WHO guidelines and about 41% of the world’s population resides in drylands: the association between dust events and disease, especially ND and MI cannot be overlooked (WHO, 2016). Poor people in global drylands, where dust events are most prevalent, are numerous and particularly vulnerable to their adverse effects (Middleton and Kang, 2017). About half of all dryland inhabitants on Earth are poor, about a billion people in total, and they have been dubbed the “forgotten billion” because they have habitually been neglected in development processes (Middleton and Kang, 2017). Public policies and individual actions are essential to reduce the human health effects of dust events. Examples include physical wind erosion control measures – which could be accomplished by paving streets and reforestation of eroded lands in parks and open areas in Cd. Juarez; avoiding exertion and outdoor activities during a DE; wearing a mask and eye coverings sufficient to reduce dust exposure on days with increased particulate matter counts or wind speed, even inside a building; and improving household insulation by detecting air leaks, substituting drafty windows and doors by sealed ones or by fixing them to reduce dust exposure (but following precautions to ventilate the area when dust events are not active, to prevent transmission of contagious diseases).

The findings of this study have several implications for future research on dust exposures and health. A future study could consider both ED visits and HA together, as well as PM\(_{2.5}\) and PM\(_{10}\) together, in order to perform comparisons of potential similarities or differences and to have a broader examination of air pollution associations in the area. It is necessary to capture information about acute exposures occurring over even shorter periods of time than an hour, in order to estimate the immediate health effects that coarse PM could be causing. Other future studies could consider
access to healthcare for those with low-medium income during a blowing dust event in El Paso and could evaluate the relationship between suicides and crime levels during dust events.

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Chapter 5: Summary and Conclusions

In this study I did an interdisciplinary assessment of the impact of dust episodes on hospitalizations in El Paso, Texas, a city with Köppen climate classification type BW. I started with an execution of a predictive model analyzing most factors influencing hospitalizations during dust events followed by the development of an intelligent tool using Case-based Algorithm in order to improve the ambulance routing demand in El Paso County. I also studied the associations of dust exposure with all ICD-9 category hospitalizations in El Paso including neurodegenerative diseases, mental illness, Valley fever, aggregated diseases, and the effects that socioeconomic status (SES) and demographic factors play in this association.

In Aim 1, I characterized a preliminary predictive model to analyze most factors influencing hospitalizations during dust events in El Paso, Texas, a society with Köppen climate classification type BW. It was be done by developing a conceptual model with all predictive variables and model equations.

The predictive model was able to describe factors related to hospitalization during blowing dust events in El Paso in order to predict future hospitalization rates based on dust events. This model was applied to establish a basic model to explore the associations between the predictor variable (elevated PM levels) and response variables (mental health and other types of hospital admissions). This model analysis may be applied using data mining in other arid locations.

In this first analysis I showed that from 2010-2014 there were more hospitalizations in a day with a DE (62%) than in a regular day (RD) (38%). During days with a DE there was a factor of 0.4 more hospitalizations due to acute conditions; 0.4 more from chronic conditions and 0.5
more from mental health than in a regular day. In addition, the top high-risk reasons for hospitalizations were births, respiratory diseases (pneumonia, obstructive chronic bronchitis, asthma), mental disorders (unspecified episodic mood disorder, cerebral artery occlusion, unspecified with cerebral infarction, schizo-affective type schizophrenia unspecified state); cardiovascular diseases (other chest pain, coronary atherosclerosis of native coronary artery, atrial fibrillation); infectious diseases affected by bacteria, virus, or due to inflammation (urinary tract infection, acute pancreatitis, acute appendicitis without mention of peritonitis); causes of injury and poisoning; complications of pregnancy, childbirth, & the puerperium; diseases of the circulatory system; diseases of the digestive system; and diseases of the genitourinary system.

In Aim 2, an intelligent tool was developed using Case-based Algorithm based on Ant Colony Algorithm and the programming language Java (J2SE). A graph was created for the central area covering the UMC Hospital in El Paso with a total of 2451 streets, avenues and boulevards (edges) and 1710 nodes.

It was determined that the proposed algorithm of Ant Colony System (bioinspired algorithm to create routes of vehicles to attend emergencies) helps to improve the ambulance routing demand due to its probable high demand during and after a dust event in El Paso County. Using Bluetooth, it is possible to use our proposed model of ambulances in an emergency related to a severe dust storm. In addition, a Kriging Model of incidence with birth cases (single liveborn, delivered by cesarean section) was performed, and shows that in the predicted future of increasing dust storms (Tong et al., 2017) there will be a necessity of more ambulances to transport more patients during a dust storm.
A comparison of the algorithm used with relation to a PSO Algorithm, and a Cultural Algorithm was performed. Our algorithm improves by 22% the performance of PSO Algorithm and by 37% the performance of Cultural Algorithms. In future research, it is important to describe the different times in other quadrants of the city in the border zone which covers hospitals and covers only the 48.7% of territorial space of the city.

As for future work, it would be important to implement the evaporation of the pheromone, find benchmarks that are being used at international level and prove to those instances of the problem, replicate the project using Java (J2ME) for the system to operate on mobile devices which provide advantages to the system in units of El Paso Health System hospitals. It will help to make this intelligent tool accessible from any device including cellphones with different screen size and reorganizing the correct decisions in a mobile device.

In Aim 3, the relationship was assessed between dust exposure (DE) of 100μg/m³ increments in maximum PM₁₀ and/or 10mph daily maximum wind speed increase and hospital admissions with different lag structures, including a single-day lag (current day [lag0]), and the following 1-7 day ([lag1-lag7]) in El Paso, TX. The regression model assuming an overdispersed Poisson distribution was used, and the relative risk rate was estimated.

It was found that the hospitalizations due to Valley fever, Coronary Atherosclerosis, Genitourinary Diseases, Neurodegenerative Diseases, Injury and Poisoning, Chemotherapy, Septicemia, Aftercare services, Circulatory System Diseases, Injury and Poisoning, Respiratory System Diseases, Associated Diseases (independently and aggregated effect of the most frequent hospitalizations associated with at least 5% of hospitalizations), Births, and all ICD-9 categories were significantly positively associated with dust exposure (through increases of at least 100
micrograms per cubic meter of daily maximum hourly PM$_{10}$, and/or increases of at least 10 mph in daily hourly average wind speed) in El Paso, Texas between 2010 and 2014, at different lag periods after exposure, indicated from higher to lower risk.

With these results it is important to inform the El Paso residents and health care community of the increased hospitalization risk due to the many causes listed above during a dust exposure day. Health care providers should be informed of the need in patients with medium and low socio-economic status to pay for their chemotherapy services; circulatory system diseases; aftercare services; and injury and poisoning associated with a dust exposure.

**Comparison of Results for Aims 1 and 3**

For Aim 1, concentration of PM$_{10}$ above 150 μg/m$^3$ and average wind speeds of 10 mph were the conditions during an hour of the day to describe the day as a dust event. Based on these conditions, there were more hospitalizations during a day with a dust event (DE) than hospitalizations during a regular day with no dust event. The dataset showed an increase in hospitalizations during the eight days after a DE and emphasized the possible effect of PM exposure during these events on hospitalizations; the effect of a DE on hospitalizations appeared to be highest during the actual day of the DE and the effect decreases after that. This effect can be observed in Aim 3 for the AD relative risk chart in which the day of a dust exposure and the following two days have a significant increase of AD hospitalizations.

The difference in the results of Aim 1 and Aim 3 may be due to differing definitions of dust event/exposure and a difference in the statistical analyses. Aim 1 compares the ‘total count’ of hospitalization during DE days with one during AD, while Aim 3 focuses on ‘daily count’ of hospitalization during DE days. In the model of Aim 3, we consider long-term temporal trend and seasonal effect as well by using smoothing function of time.
Future Recommendations

Recommendations for reduction of outdoor and indoor exposures to DEs should be generated for El Paso County. These recommendations could be in audiovisual messages in prominent spots for their implementation, tailored according to their audience. Improvement of early warning dust forecasting from meteorology modelers is needed in order to disseminate warnings and recommendations to reduce exposure to dust events and to alert patients with associated diagnoses about upcoming sand and dust storm events in an early manner.

A future study could consider both emergency department visits and hospital admissions together, in order to perform comparisons of potential similarities or differences and to have a broader examination of air pollution associations in the area. It is necessary to capture information about acute exposures occurring over even shorter periods of time than an hour, in order to estimate the health effects that coarse PM could be causing. Other future studies could consider access to healthcare for those with low-medium income during a blowing dust event in El Paso and could evaluate the relationship between suicides and crime levels during dust events. Expand the study to the Southern High Plains of West Texas (Counties of Lubbock and Midland: City of Amarillo) where DE are common. Creation of web-based user interfaces and mobile applications should be considered to increase accessibility to dust event precautions on daily basis. Other studies could assess the areas with significantly more DE-associated hospitalizations in El Paso County via Kriging Model in GIS and use data mining to further analyze the characteristics of patients affected by a DE.

Public policies and individual actions are essential to reduce the human health effects of dust events. Examples include physical wind erosion control measures – which could be accomplished by paving streets and reforestation of eroded lands in parks and open areas in Cd.
Juarez; avoiding exertion and outdoor activities during a DE; wearing a mask and eye coverings sufficient to reduce dust exposure on days with increased particulate matter counts or wind speed, even inside a building; and improving household insulation by detecting air leaks, substituting drafty windows and doors by sealed ones or by fixing them to reduce dust exposure (but following precautions to ventilate the area when dust events are not active, to prevent transmission of contagious diseases).
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Vita

Estrella De Jesus Herrera-Molina was awarded a Bachelor of Science degree in Environmental Engineering in University of Chihuahua at Chihuahua (UACH) in 2001. Funding for her research “Characterization of Climatic Zones in the State of Chihuahua” was provided in the last year by SAGARPA. After graduating she worked at a consulting company in Cd. Juarez. In 2005 she was awarded a master’s degree in Interdisciplinary Studies from the University of Texas at El Paso. Her research “Implications of Airborne PM$_{2.5}$ and Nitrogen Dioxide Measured at Elementary Schools in Cd. Juárez, Mx.” was funded by the EPA. After graduating she worked at Texas Agricultural Experiment Station at Texas A&M University System at El Paso, TX as a research assistant in water management. After that she worked at several consulting companies. In 2015 she was admitted into the Environmental Science and Engineering (ESE) doctoral program at the University of Texas at El Paso. Funding for her support was provided by the teaching assistance program of the ESE doctoral program. She presented her research at the 17th Mexican International Conference on Artificial Intelligence, MICAI 2018, Guadalajara, Mexico and won first place in investigation. She presented a research poster at the New Mexico Dust Conference in 2020. Based on her research she has published two articles and has another two in preparation. While in her doctoral program she worked as a teaching assistant at the University of Texas at El Paso. She assisted in air pollution, geology, hydrology, biology and climatologic classes and helped students to succeed in their laboratories and assignments.

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