2021-08-01

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

Estrella de Jesus Herrera-Molina
University of Texas at El Paso

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

ESTRELLA DE JESUS HERRERA-MOLINA

Doctoral Program in Environmental Science and Engineering

APPROVED:

Thomas E. Gill, Ph.D., P.G., F.R.G.S.

Gabriel Ibarra-Mejia, MD, PhD, MsErg

Craig E. Tweedie, Ph.D.

Soyoung Jeon, Ph.D.

Alberto Ochoa Zezzatti, Ph.D., P.E.

Stephen L. Crites, Jr., Ph.D.
Dean of the Graduate School

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

August 2021

Acknowledgements

I would like to acknowledge everyone who made this research possible. I thank profusely my dissertation committee members, who each provided patient advice, guidance, dedication, interest and overwhelming help throughout the research process. My deepest gratitude to my committee chair, Thomas E. Gill, Ph.D., P.G., F.R.G.S., Professor from the Department of Earth, Environmental and Resource Sciences for his meticulous scrutiny, advice, knowledge of the complex world of the dust, and scientific approach which has helped me to accomplish this study. Special thanks to Gabriel Ibarra-Mejia, MD, Ph.D., MsErg, assistant professor in the Public Health Sciences at UTEP for his advice in epidemiology, support and meticulous scrutiny in this study. Special thanks to Dr. Alberto Ochoa Zezzatti, Ph.D., P.E., Professor in Artificial Intelligence at UACJ for his vast support in data mining and research guidance. I am very thankful to Dr. Soyoung Jeon, Ph.D., for statistical support.

I am extremely thankful to Dr. Hector Olvera for his guidance, advice and contribution to this project. I am very thankful to Dr. Amy Wagler and William Marfo, M.S. for statistical support. I am extremely thankful to Dr. Karin Ardon-Dryer from the Department of Geosciences, Atmospheric Science Group at Texas Tech University, Lubbock TX. for her data contribution to this project, in addition to Dr. Tarek Kandakji from the Department of Geosciences, Texas Tech University for his contribution to this project. To the members of the PhD Environmental Science and Engineering program especially to Dr. Craig Tweedie, ESE director and Lina Hamdan, ESE program coordinator for their kindness and support. It is my privilege to thank my husband Carlos Herrera for his constant encouragement and advice throughout my research project and to my children Celeste and Gadiel Herrera for their kindness and support.

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 μg/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.

Table of Contents

List of Tables

List of Figures

THE UNIVERSITY OF TEXAS AT EL PASO
Office of the Vice President for Research and Sponsored Projects
Institutional Review Board
El Paso, Texas 79968-0587
phone: 915 747-8841 fax: 915 747-5931

FWA No: 00001224

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.

Exempt protocols do not need to be renewed. Please note that it is the Principal Investigator's responsibility to resubmit the proposal for review if there are any modifications made to the originally submitted proposal. This review is required in order to determine if "Exemption" status remains.

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 $\mu g/m^3$ and wind speed >10 mph. For example, on January 16th of 2012, the visibility was reduced to 1.3 miles with a wind speed of 14.8 mph, and PM_{10} of 141.1 $\mu g/m^3$. 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 at el., 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 at el., 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).

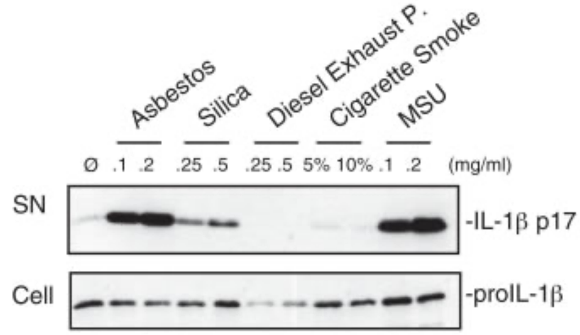

Figure 1. 1 Silica activates IL-1B secretion in human macrophages. Analyzed in media supernatants (SN) and in cell extracts (Cell). From Dostert et al. (2008)

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 SiO_2 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 SiO_2)" 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".

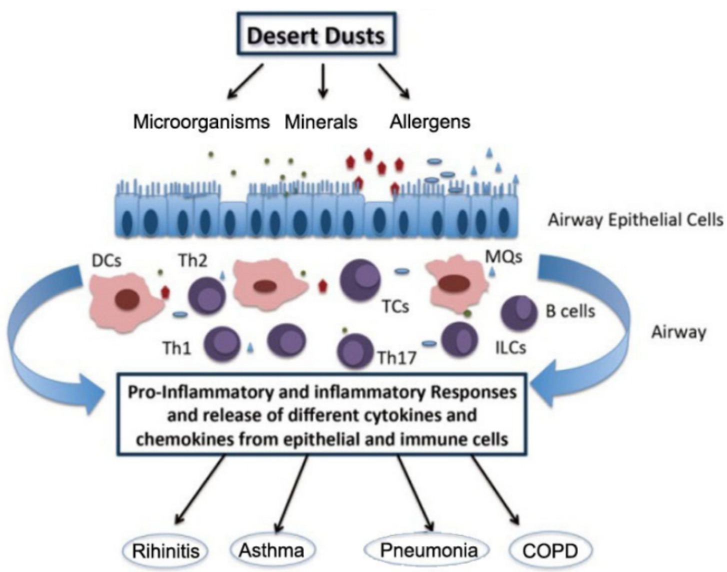

Figure 1. 2 Systemic inflammation mechanism due to desert dust. Diagram shows how desert dusts affect the respiratory and immune systems by causing a direct effect to the alveolar walls and epithelial cells; by influencing the oxidative stress; and release of pro-inflammatory cytokines. From Zhang et 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/m^3 increments in daily maximum of hourly PM_{10} 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,

Osteoarthrosis, 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

Al, B., Bogan, M., Zengin, S., Sabak, M., Kul, S., Oktay, M. M., and Vuruskan, E. (2018). Effects of Dust Storms and Climatological Factors on Mortality and Morbidity of Cardiovascular Diseases Admitted to ED. Emergency Medicine International, 2018(Dm), 1–7. http://doi.org/10.1155/2018/3758506

Behzad, H., Mineta, K., Gojobori, T., Arabia, S., Arabia, S., Sciences, M., Gojobori, T. (2018). Global Ramifications of Dust and Sandstorm Microbiota. Genome Biology and Evolution, 10, 1970–1987. http://doi.org/10.1093/gbe/evy134/5046809

Bozlaker, A., Peccia, J., and Chellam, S. (2017). Indoor/Outdoor Relationships and Anthropogenic Elemental Signatures in Airborne PM2.5 at a High School: Impacts of Petroleum Refining Emissions on Lanthanoid Enrichment. Environmental Science & Technology, 51(9), 4851–4859. https://doi.org/10.1021/acs.est.6b06252

Chan, Y. S., Teng, J. C. Y., Liu, T. C., and Peng, Y. I. (2018). Asian dust storms and diabetes hospitalization: a nationwide population-based study. Air Quality, Atmosphere and Health, 11(10), 1243–1250. http://doi.org/10.1007/s11869-018-0623-

Disdier, C., Devoy, J., Cosnefroy, A., Chalansonnet, M., Herlin-Boime, N., and Brun, E. (2015). Tissue biodistribution of intravenously administrated titanium dioxide nanoparticles revealed blood-brain barrier clearance and brain inflammation in rat. Particle and Fibre Toxicology, 12, 27. https://doi.org/10.1186/s12989-015-0102-8

Dostert, C., Pétrilli, V., Van Bruggen, R., Steele, C., Mossman, B. T., and Tschopp, J. (2008). Innate immune activation through Nalp3 inflammasome sensing of asbestos and silica. Science, 320(5876), 674–677. http://doi.org/10.1126/science.1156995

Ebrahimi, S. J. A., Ebrahimzadeh, L., Eslami, A., and Bidarpoor, F. (2014). Effects of dust storm events on emergency admissions for cardiovascular and respiratory diseases in Sanandaj, Iran. Journal of Environmental Health Science and Engineering, 12(1), 1–5. http://doi.org/10.1186/s40201-014-0110-x

EPA, a (2018, July 20). Reference News Release: Oil Refiners to Reduce Air Pollution at Six Refineries Under Settlement with EPA and Department of Justice. Retrieved from https://www.epa.gov/enforcement/reference-news-release-oil-refiners-reduce-air-pollution-six-refineries-under-settlement.

Gill, T.E., Stout, J.E., and Peinado, P. (2009). Composition and characteristics of aerosols in the Southern High Plains of Texas, USA. AIP Conference Proceedings, 1099, 255- 258.

Grineski, S. E., Staniswalis, J. G., Bulathsinhala, P., Peng, Y., and Gill, T. E. (2011). Hospital admissions for asthma and acute bronchitis in El Paso, Texas: Do age, sex, and insurance status modify the effects of dust and low wind events? Environmental Research, 111(8), 1148–1155. http://doi.org/10.1016/j.envres.2011.06.007

Hand, J. L., White, W. H., Gebhart, K. A., Hyslop, N. P., Gill, T. E., and Schichtel, B. A. (2016). Earlier onset of the spring fine dust season in the southwestern United States. Geophysical Research Letters, 43(8), 4001–4009. http://doi.org/10.1002/2016GL068519

Jiang, C., Lam, T. H., Xu, L., Lin, Q., Cheng, K. K., and Jin, Y. L. (2014). Past occupational dust exposure, depressive symptoms and anxiety in retired Chinese factory workers: The Guangzhou Biobank Cohort Study. Journal of Occupational Health, 56, 444- 452.

Kanatani, K. T., Ito, I., Al-Delaimy, W. K., Adachi, Y., Mathews, W. C., Ramsdell, J. W., and Yamamoto, J. (2010). Desert dust exposure is associated with increased risk of asthma hospitalization in children. American Journal of Respiratory and Critical Care Medicine, 182(12), 1475–1481. http://doi.org/10.1164/rccm.201002-0296OC

Keil, D. E., Buck, B., Goossens, D., Teng, Y., Pollard, J., McLaurin, B., and DeWitt, J. (2016a). Health effects from exposure to atmospheric mineral dust near Las Vegas, NV, USA. Toxicology Reports, 3, 785–795. http://doi.org/10.1016/j.toxrep.2016.09.009

Keil, D.E., Buck, B., Goossens, D., Teng, Y., Spencer, M., Murphy, L., and DeWitt, J. (2016b). Immunotoxicological and neurotoxicological profile of health effects following subacute exposure to geogenic dust from sand dunes at the Nellis Dunes Recreation Area Las Vegas, NV. Toxicology and Applied Pharmacology, 291, 1–12.

Keil, D. E., Buck, B., Goossens, D., McLaurin, B., Murphy, L., Leetham-Spencer, M., and DeWitt, J. C. (2018). Nevada desert dust with heavy metals suppresses IgM antibody production. Toxicology Reports, 5, 258–269. http://doi.org/10.1016/j.toxrep.2018.01.006

Khan, R. K., and Strand, M. A. (2018). Road dust and its effect on human health: a literature review. Epidemiology and Health, 40, e2018013. http://doi:10.4178/epih.e2018013

Khaniabadi, Y. O., Fanelli, R., De Marco, A., Daryanoosh, S. M., Kloog, I., Hopke, P. K., and Goudarzi, G. (2017). Hospital admissions in Iran for cardiovascular and respiratory diseases attributed to the Middle Eastern Dust storms. Environmental Science and Pollution Research, 24(20), 16860–16868. http://doi.org/10.1007/s11356-017-9298-5

Kolavali, S. R. and Bhatnagar, S. (2009). Ant colony optimization algorithms for shortest path problems, in Network Control and Optimization, Lecture Notes in Computer Science, Springer-Verlag, Berlin. vol. 5425, pp. 37-44.

Lee, J. A., and Gill, T. E. (2015). Multiple causes of wind erosion in the Dust Bowl. Aeolian Research, 19, 15–36. http://doi.org/10.1016/j.aeolia.2015.09.002

Lee, J. A., Gill, T. E., Mulligan, K. R., Dominguez Acosta, M., and Perez, A. E. (2009). Land use/land cover and point sources of the 15 December 2003 dust storm in southwestern North America. Geomorphology, 105(1–2), 18–27. https://doi.org/10.1016/j.geomorph.2007.12.016

Lee, J. A., Baddock, M. C., Mbuh, M. J., and Gill, T. E. (2012). Geomorphic and land cover characteristics of aeolian dust sources in West Texas and eastern New Mexico, USA. Aeolian Research, 3(4), 459–466. http://doi.org/10.1016/j.aeolia.2011.08.001

Liu, X., Sui, B., and Sun, J. (2017). Blood-brain barrier dysfunction induced by silica NPs in vitro and in vivo: Involvement of oxidative stress and Rho-kinase/JNK signaling pathways. Biomaterials, 121, 64-82. https://doi.org/10.1016/j.biomaterials.2017.01.006.

Meng, Z., and Lu, B. (2007). Dust events as a risk factor for daily hospitalization for respiratory and cardiovascular diseases in Minqin, China. Atmospheric Environment, 41(33), 7048–7058. https://doi.org/10.1016/j.atmosenv.2007.05.006

Mohammad, S.R., Mei Y., Hamilton M., Salim F. D. (2017). CAPRA: A contour-based accessible path routing algorithm, Information Sciences, 385–386, 157-173.

Morman, S. A., and Plumlee, G. S. (2013). The role of airborne mineral dusts in human disease. Aeolian Research, 9, 203–212. http://doi.org/10.1016/j.aeolia.2012.12.001

Morman, S.A. and Plumlee, G.S. (2014). Dust and human health. In: Knippertz, P., and Stuut, J.B.W., Mineral Dust A Key Player In The Earth System, Springer, pp. 385-409.

Nery, L. E., Florencio, R. T., Sandoval, P. R. M., Rodrigues, R. T., Alonso, G., and Mason, G. R. (1993). Additive effects of exposure to silica dust and smoking on pulmonary epithelial permeability: A radioaerosol study with technetium-99m labelled DTPA. Thorax, 48(3), 264–268. http://doi.org/10.1136/thx.48.3.264

Novlan, D. J., Hardiman, M., and Gill, T. E. (2007). A Synoptic Climatology of Blowing Dust Events in El Paso, Texas from 1932-2005. Preprints, American Meteorological Society Annual Meeting, 16th Conference on Applied Climatology, J3.12.

Oil Change International, (2018, July 5). Refineries. http://refineryreport.org/refineries.php

Prospero, J.M., Ginoux, P., Torres, O., Nicholson, S.E. and Gill, T.E. (2002). Environmental characterization of global sources of atmospheric soil dust identified with the Nimbus 7 Total Ozone Mapping Spectrometer (TOMS) absorbing aerosol product. Reviews of Geophysics, 40, 2-1- 2-31. https://doi: 10.1029/2000RG000095

Rivera Rivera, N. I., Gill, T. E., Bleiweiss, M. P., and Hand, J. L. (2010). Source characteristics of hazardous Chihuahuan Desert dust outbreaks. Atmospheric Environment, 44(20), 2457–2468. https://doi.org/10.1016/J.ATMOSENV.2010.03.019

Rodopoulou, S., Chalbot, M. C., Samoli, E., DuBois, D. W., San Filippo, B. D., and Kavouras, I. G. (2014). Air pollution and hospital emergency room and admissions for cardiovascular and respiratory diseases in Doña Ana County, New Mexico. Environmental Research, 129, 39–46. http://doi.org/10.1016/j.envres.2013.12.006

Schreibelt, G., Kooij, G., Reijerkerk, A., van Doorn, R., Gringhuis, S.I., and van der Pol, S. (2007). Reactive oxygen species alter brain endothelial tight junction dynamics via RhoA, PI3 kinase, and PKB signaling. FASEB Journal, 21, 3666-3676.

Schweitzer, M. D., Calzadilla, A. S., Salamo, O., Sharifi, A., Kumar, N., Holt, G., and Mirsaeidi, M. (2018). Lung health in era of climate change and dust storms. Environmental Research, 163, 36–42. http://doi.org/10.1016/j.envres.2018.02.001

Shao, Y. (2008). Physics and modelling of wind erosion (2nd edition). Heidelberg: Springer.

Sharma, H.S., Muresanu, D.F., Patnaik, R., and Sharma, A. (2013) Exacerbation of brain pathology after partial restraint in hypertensive rats following SiO(2) nano-particles exposure at high ambient temperature. Molecular Neurobiology, 48, 368-379.

Sharma, H.S., Patnaik, R., Sharma, A., Sjöquist, P.O., and Lafuente J.V. (2009). Silicon dioxide nanoparticles (SiO_2, 40-50 nm) exacerbate pathophysiology of traumatic spinal cord injury and deteriorate functional outcome in the rat. An experimental study using pharmacological and morphological approaches. The Journal of Nanoscience and Nanotechnology, 9(8), 4970-4980.

Staniswalis, J.G., Parks, N.J., Bader, J.O. and Muñoz-Maldonado, Y. (2005). Temporal Analysis of Airborne Particulate Matter Reveals a Dose-Rate Effect on Mortality in El Paso: Indications of Differential Toxicity for Different Particle Mixtures, Journal of the Air & Waste Management Association, 55:7, 893-902, DOI: 10.1080/10473289.2005.10464696

Talarico, L., Meisel, F., and Sörensen, K. (2014). Ambulance routing for disaster response with patient groups. Computers & Operations Research, 56, 120- 133. DOI:10.1016/j.cor.2014.11.006.

Tong, D.Q., Wang, J.X.L., Gill, T.E., Lei, H., and Wang, B.Y. (2017). Intensified dust storm activity and valley fever infection in the southwestern United States. Geophysical Research Letters, 44(9), 4304–4312.

Van Pelt, R. S., and Zobeck, T. M. (2007). Chemical constituents of fugitive dust. Environmental Monitoring and Assessment, 130(1–3), 3–16. http://doi.org/10.1007/s10661-006-9446-8

Yamashita, K., Yoshioka, Y., Higashisaka, K., Mimura, K., Morishita, Y., and Nozaki, M. (2011). Silica and titanium dioxide nanoparticles cause pregnancy complications in mice. Nature Nanotechnology, 6, 321-328.

Yu, H. L., Chien, L. C., and Yang, C. H. (2012). Asian dust storm elevates children's respiratory health risks: A spatiotemporal analysis of children's clinic visits across Taipei (Taiwan). PLoS ONE, 7(7), 1–9. http://doi.org/10.1371/journal.pone.0041317

Zhang B., Chen L., Choi J.J., Hennig B., and Toborek M. (2012) Cerebrovascular toxicity of PCB153 is enhanced by binding to silica nanoparticles. The Journal of Neuroimmune Pharmacology, 7, 991-1001.

Zhang, X., Zhao, L., Tong, Q. D., Wu, G., Dan, M., and Teng, B. (2016). A Systematic Review of Global Desert Dust and Associated Human Health Effects. Atmosphere,7(12), 158. http://doi.org/10.3390/atmos7120158

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.

ISSN 1870-4069

Conceptualization of a Predictive Model for Analysis of the Health Outcomes of Dust Events in a Society with Köppen Climate Classification BW

Estrella Molina-Herrera[1], Alberto Ochoa[2,3], Thomas Gill[1], Gabriel Ibarra-Mejia[1], Carlos Herrera[1]

[1] University of Texas at El Paso, El Paso, TX, USA
[2] The Autonomous University of Ciudad Juarez, Chihuahua, Mexico
[3] El Paso VA Health Care System, TX, USA*

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 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 PM10 above 4000 $\mu g/m^3$ with near zero visibility due to these natural events (Rivera et al., 2010), thus exceeding the primary and secondary 24-hour standard of 150 $\mu g/m^3$. 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),

Conceptualization of a Predictive Model for Analysis of the Health Outcomes of Dust Events in a Society with Köppen Climate Classification BW

Estrella Molina-Herrera[1], Alberto Ochoa[2], Thomas Gill[1], Gabriel Ibarra-Mejia[1], Carlos Herrera[1,3]
[1] University of Texas at El Paso, El Paso, TX, USA
[2] The Autonomous University of Ciudad Juarez, Chihuahua, Mexico
[3] El Paso VA Health Care System, El Paso, TX, USA

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.

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 $\mu g/m^3$ with near zero visibility due to these natural events (Rivera et al., 2010), thus exceeding the primary and secondary 24-hour standard of 150 $\mu g/m^3$. 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 at 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 $\mu g/m^3$ 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 $\mu g/m^3$.

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_{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_{10} above 150 $\mu g/m^3$ 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.

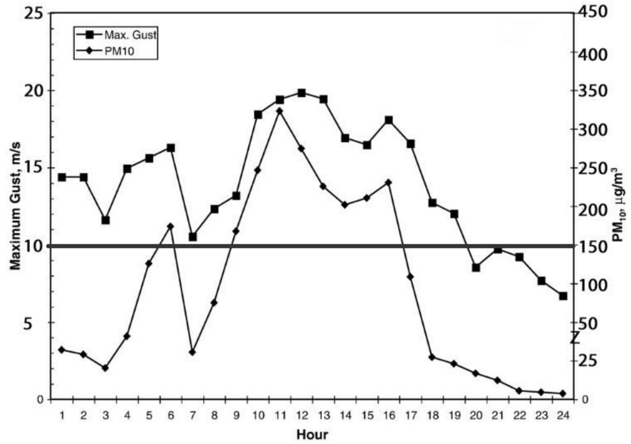

Figure 2. 1 Definition of a Dust Event for this study; Wind speed above 10m/h and PM_{10} above 150 $\mu g/m^3$.

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 $\mu g/m^3$ and for $PM_{2.5}$ 288.33 $\mu g/m^3$ (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 airconditioner 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).

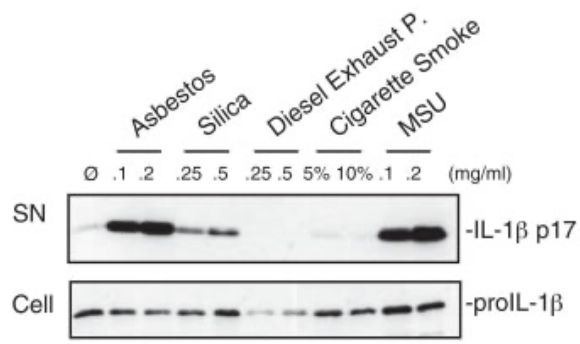

Figure 2. 2 Silica activate IL-1B secretion in human macrophages. Analyzed in media supernatants (SN) and in cell extracts (Cell). From Dostert et al. 2008

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 la., 2015).

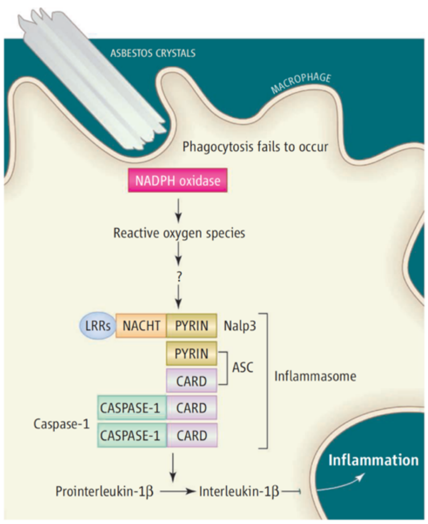

Figure 2. 3 Systemic inflammation mechanism due to DE. Asbestos crystals or silica are too large to be phagocytosed by macrophages and so are subject to "frustrated" phagocytosis. This leads to activation of NADPH oxidase and the generation of reactive oxygen species. This event activates the Nalp3 and ASC inflammasome promoting the processing and release of the potent proinflammatory molecule interleukin-1B. 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-1b 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; Morman 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 patters, extreme weather effects), environmental changes (changes in pollutant exposure, changes in allergens production, timing and distribution), urban landscapes, emission patters), 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 (∘ 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. 1 Codes from the International Classification of Diseases, Ninth Revision (ICD)-9.

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

Model Analyses

Dust storm periods will be identified by matching the hourly average PM_{10} exceeding 150 $\mu g/m^3$ 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).

$$\alpha = i\,(\gamma+\delta+\varepsilon+\iota) \pm id, \tag{1}$$

Where Educational attainment (α) is defined by: γ= Neighborhood, δ= Access to education, ε= Parent expectations about children, ι= 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 ι= Income (value given from the Census Block Group code at the El Paso County and projected values for 2020 and 2050).

$$Z=(\zeta)^{gi} \tag{2}$$

Where Occupation (Z) is defined by: ζ=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.

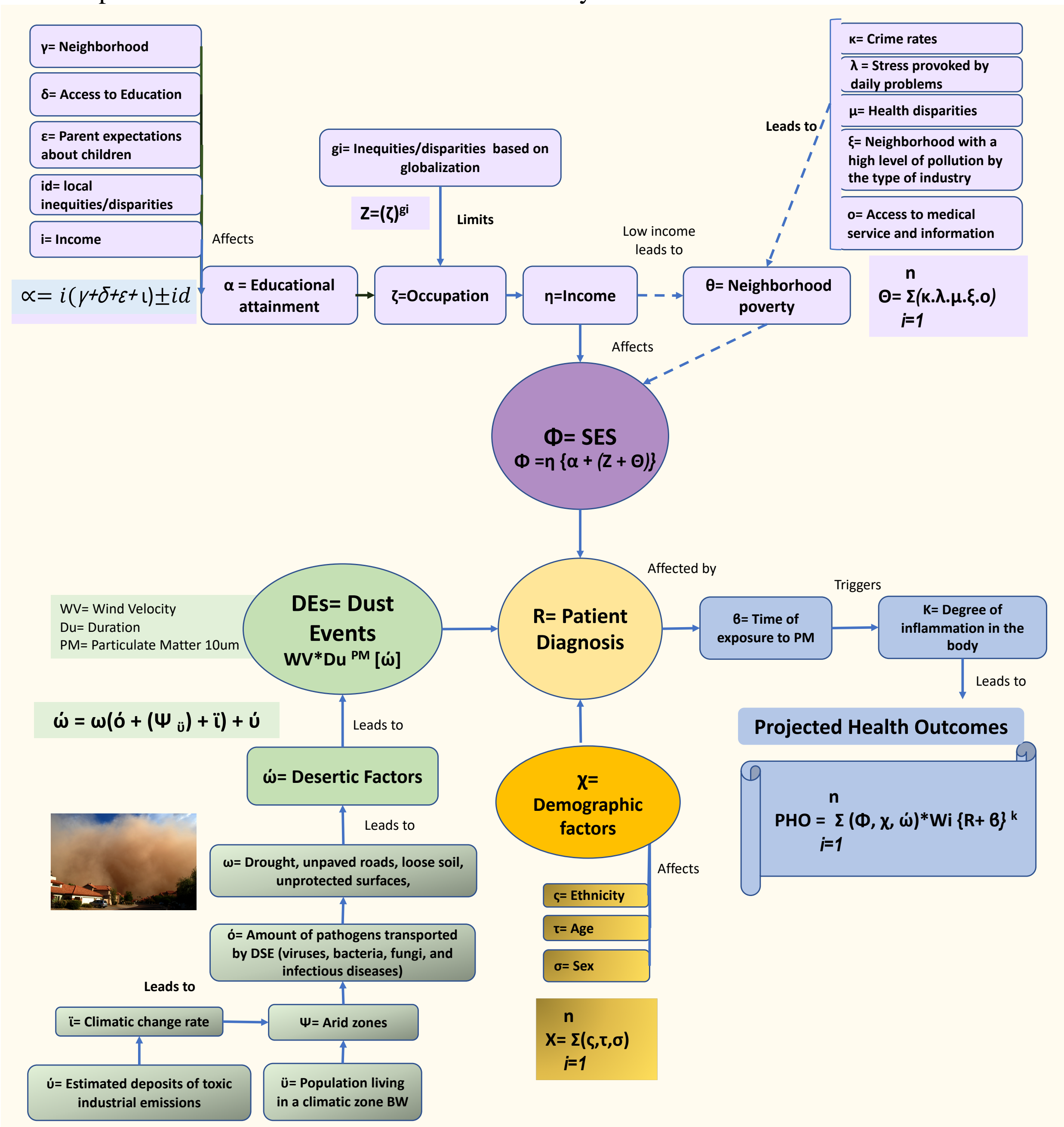

Figure 2. 4 Conceptual predictive model of DEs and its health outcomes in a society of BW climate.

$$\Theta = \sum_{i=1}^{n} (\kappa.\lambda.\mu.\xi.o.), \tag{3}$$

Where Neighborhood poverty (θ) is defined by: $\varkappa$= crime rates, λ = stress provoked by discrimination, μ= health disparities, ξ= Neighborhood with a certain level of pollution according to the type of industry and o= access to medical service and information.

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

Where SES (Φ) is defined by: η= income, α = Educational attainment, Z= Occupation, θ= Neighborhood poverty.

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

Where Demographic Factors (χ) is defined by: ς= Ethnicity, τ= Age and σ= Sex.

$$\acute{\omega} = \omega(\acute{o} + (\Psi_{\ddot{\upsilon}}) + \ddot{\iota}\,) + \acute{\upsilon}, \tag{6}$$

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

$$DEs = WV * Du\ PM\ [\acute{\omega}], \tag{7}$$

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

$$PHO = \sum_{i=1,}^{n} (\Phi, \chi, \acute{\omega}) * Wi\ \{R + \beta\}^{k} \tag{8}$$

Where Projected Health Outcomes for 2030 – 2050 (PHO) is defined by: Φ= SES, χ= demographic factors, $\acute{\omega}$= DEs, R= Patient hospitalization, β= Exposure time to PM_{10} and K= Degree of inflammation in the body. In this equation, PHO refers to the Projected Health Outcomes ether for the present (2010-2014), or projections for 2030 and 2050 due to DEs: denotes the sum of Φ= SES, χ= Congenital factors and ώ= DSE; which affect the R= Patient hospitalization due to; ϐ= Exposure time to PM; and may be exacerbated by ϑ= 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 find 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 be not 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. 2 Comparison of ICD-9 diagnosis in a regular day and in a DE from 2010-2014

		Total count		
		no DSE	DSE	Total
ICD-9 diagnosis	1	3792	6375	10167
	2	3896	6467	10363
	3	4858	8177	13035
	4	1296	2275	3571
	5	5778	10111	15889
	6	1865	3175	5040
	7	11813	19653	31466
	8	8834	14550	23384
	9	11165	18833	29998
	10	6040	10141	16181
	11	16255	25880	42135
	12	2041	3310	5351
	13	4268	7429	11697
	14	444	762	1206
	15	866	1364	2230
	16	4059	6625	10684
	17	8005	13441	21446
	19	17935	28986	46921
Total		113210	187554	300764

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).

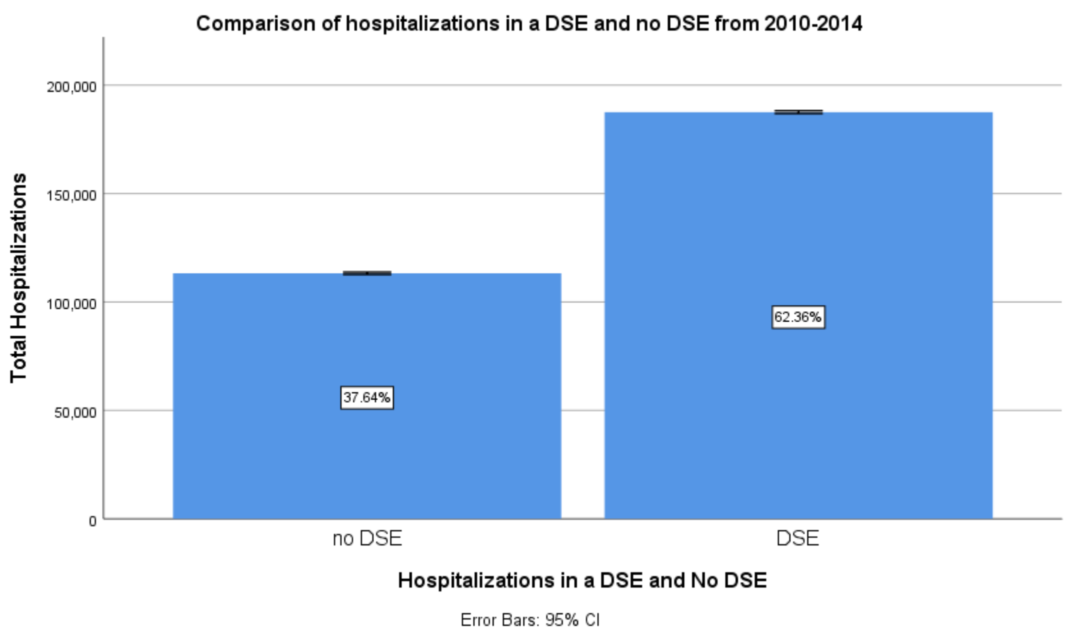

Figure 2. 5 Comparison of total hospitalizations in regular Days and DE from 2010-2014. There were more hospitalizations in a DE (62%) than in a regular day (RD) (38%).

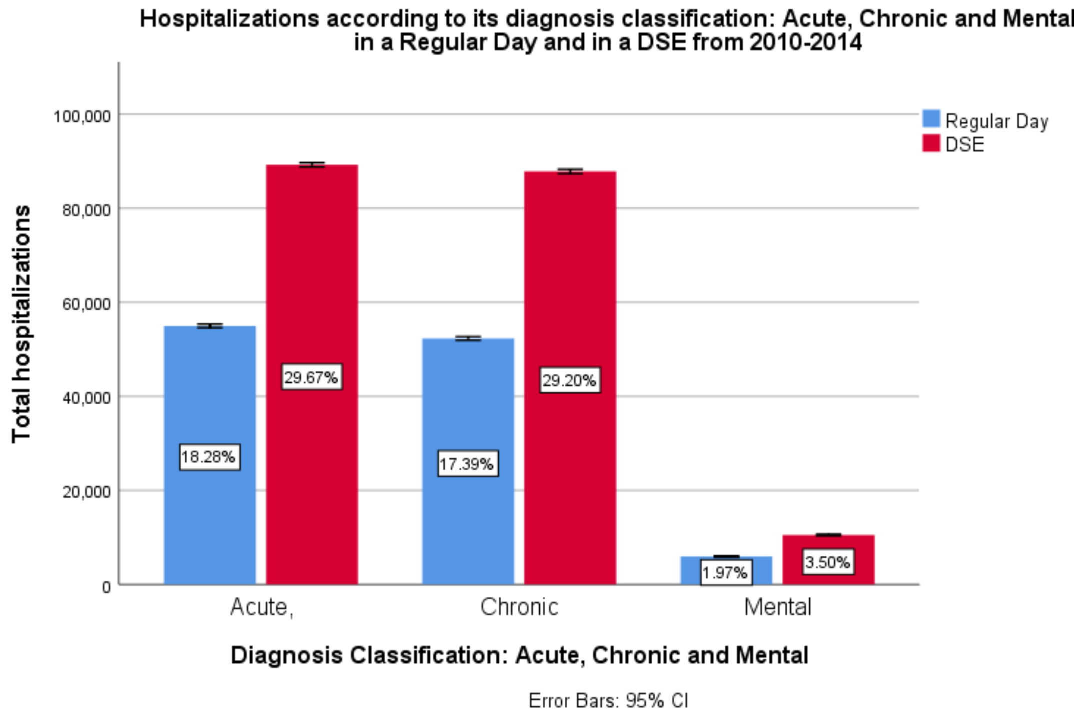

Figure 2. 6 Comparison of Acute, Chronic and Mental total Admissions code in a DE vs a regular day. During DEs there were 61.47% more hospitalizations due to acute conditions; 62.67% more from chronic conditions and 63.98% more from mental health than in a regular day from 2010-2014.

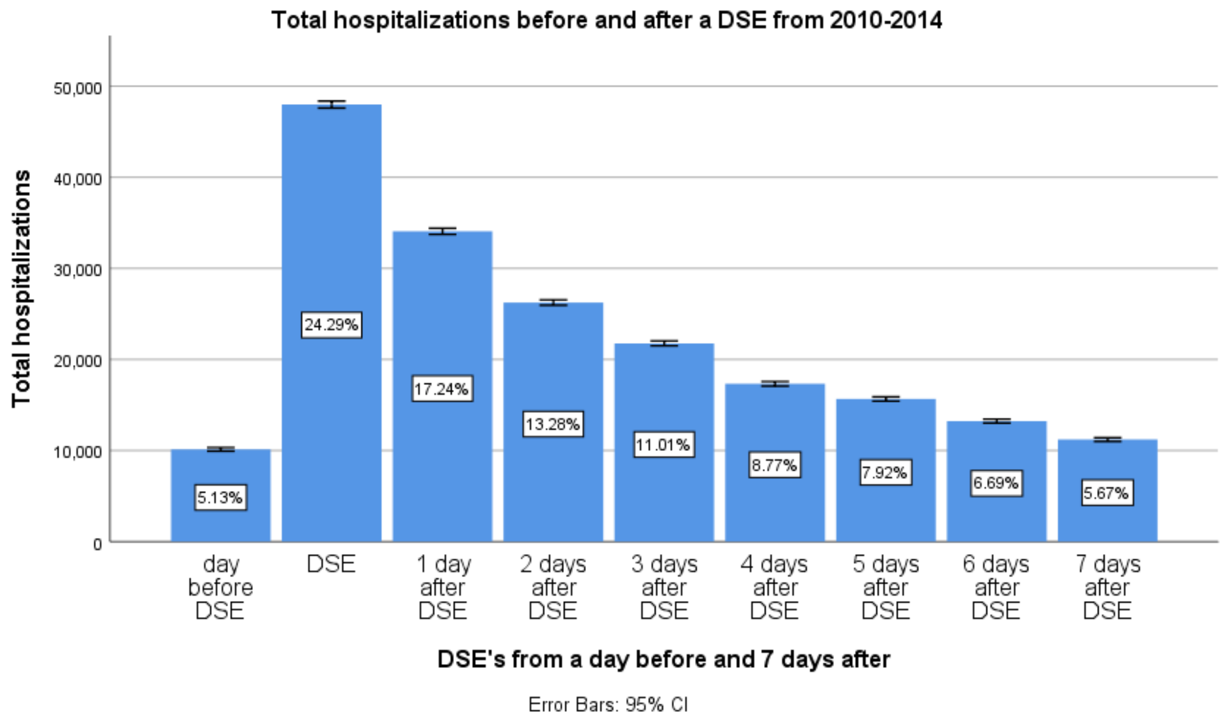

Figure 2. 7 Total Hospitalization percentage per day before and after DE (each day has many hospitalizations) from 2010-2014. There is an increase in hospitalizations after a DE and emphasized the possible effect of PM_{10} exposure during these events and hospitalizations; the effect of a DE on hospitalizations might be highest during the actual day of the DE and such effect decreases after that.

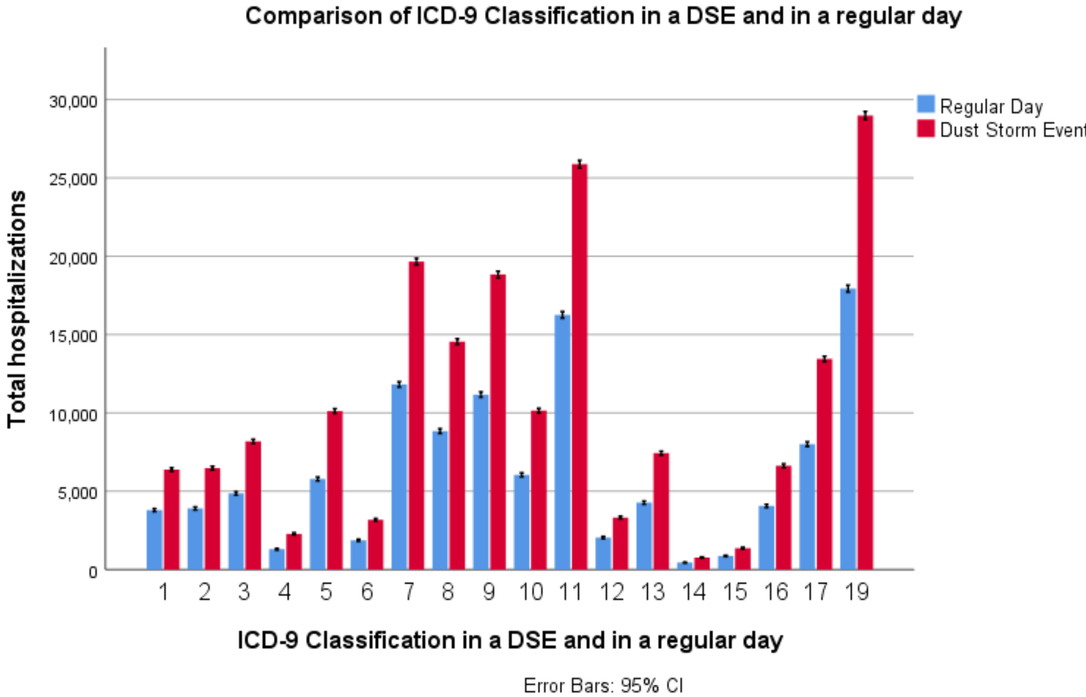

Figure 2. 8 Comparison of total IDC-9 Admissions code in a DE vs a regular day from 2010-2014. The top 7 causes of admission during a DE from 2010-2014 are: causes of injury & poisoning (15.6%), complications of pregnancy, childbirth, & the puerperium (14%), diseases of the circulatory system (10.5%), 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.

	Top reasons for hospitalizations	ICD-9
Respiratory	Pneumonia, organism unspecified	486
	Obstructive chronic bronchitis with (acute) exacerbation	491.21
	Asthma, unspecified type, with (acute) exacerbation	493.92
Mental	Unspecified episodic mood disorder	296.90
	Cerebral artery occlusion, unspecified with cerebral infarction	434.91
	Schizo-affective type schizophrenia unspecified state	295.90
Cardiovascular	Other chest pain	786.59
	Coronary atherosclerosis of native coronary artery	414.01
	Atrial fibrillation	427.31
Infection	Urinary tract infection, site not specified	599.0
	Acute pancreatitis	577.0
	Acute appendicitis without mention of peritonitis	540.9

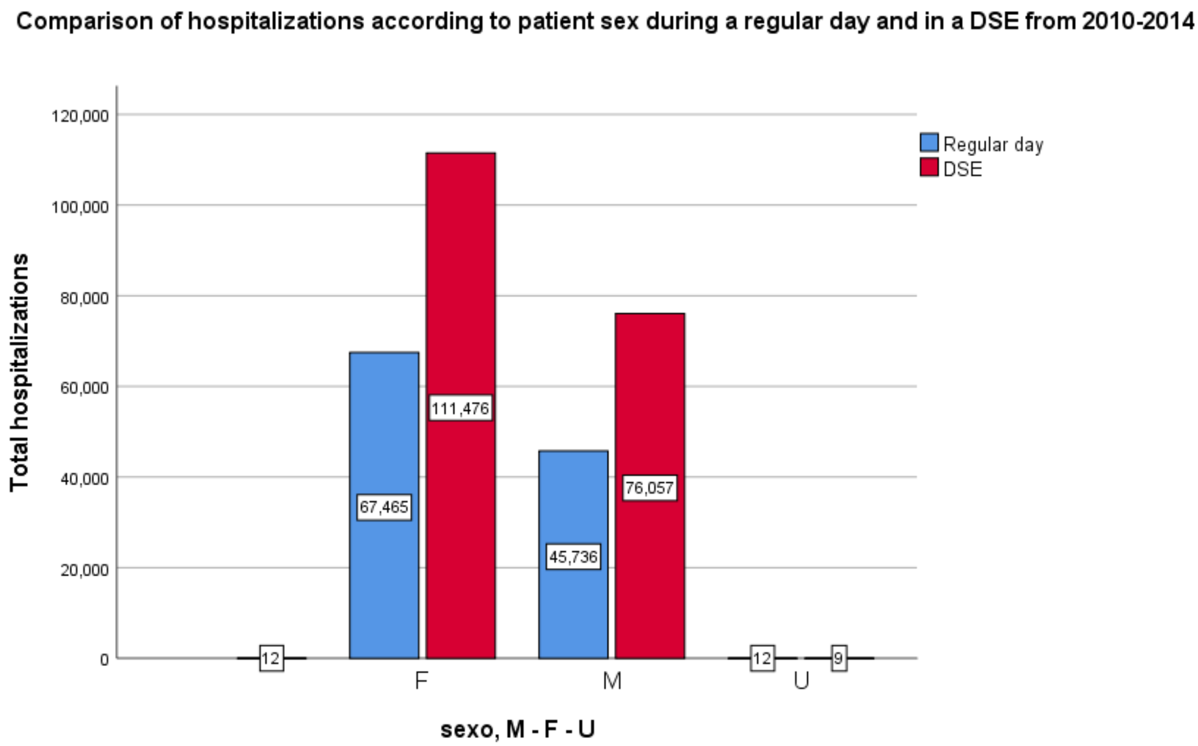

Figure 2. 9 Comparison of total hospitalizations by Female, Male and Unknown in a RD and in a DE from 2010-2014. There are 59.5% more females hospitalized than males (40.5%) during 2010-2014 at El Paso County.

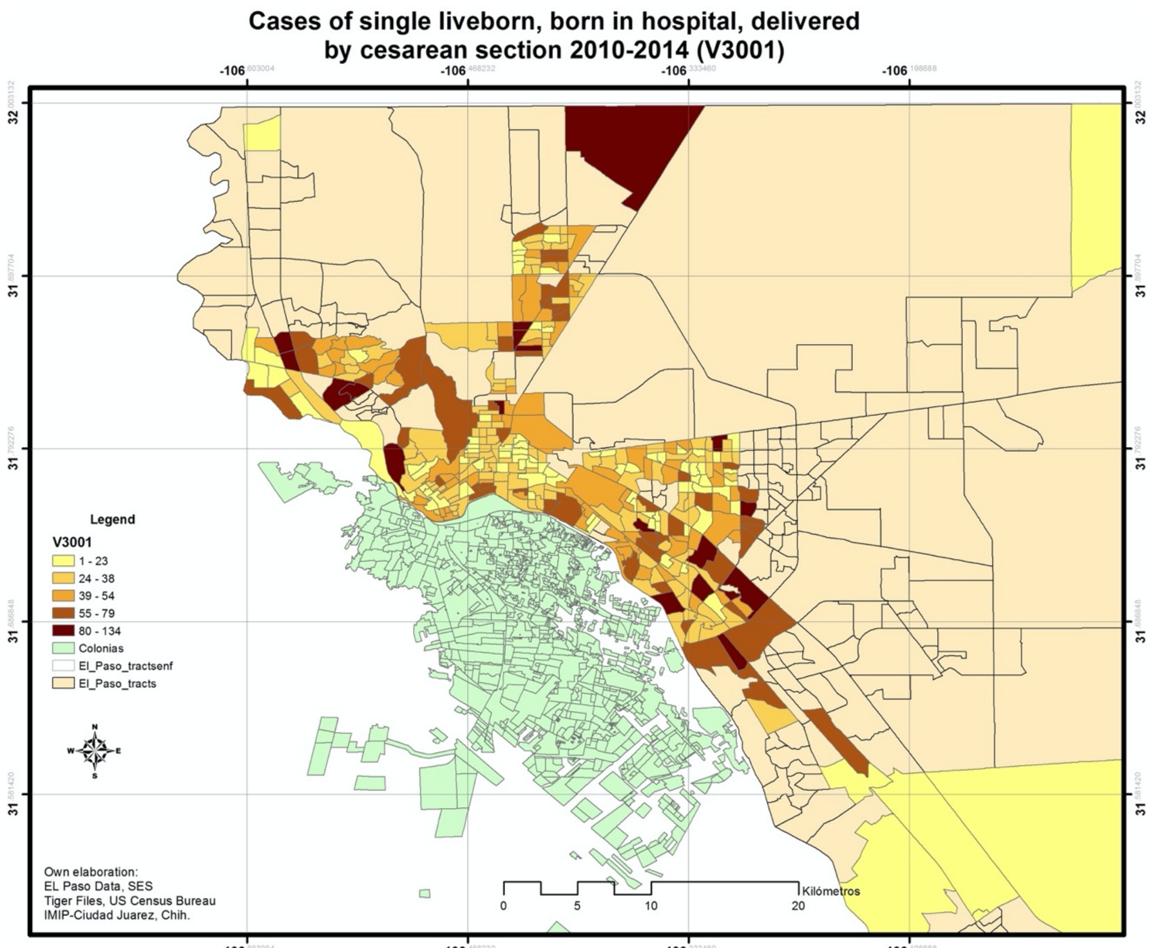

Figure 2. 10 Map of cases of single born by cesarean section during DEs at El Paso, TX from 2010-2014. More patients live in areas with heavily trafficked roads and DE shows to affect the population with all incomes but more frequent patients with a family income of <40,000 dollars; and there are more 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

1. Adler, N., Pantell, M.S.: O'Donovan, A.: Educational attainment and late life telomere length in the Health, Aging and Body Composition Study. Brain Behav. Immun. 27, 15–21 (2013).
2. Agier, L., Deroubaix, A., Martiny, N., Yaka, P., Djibo, A., & Broutin, H.: Seasonality of meningitis in Africa and climate forcing: Aerosols stand out. Journal of the Royal Society Interface, 10(79) (2013).
3. Aguilar, M., Bhuket, T., Torres, S., Liu, B., Wong, R.J.: Prevalence of the metabolic syndrome in the United States, 2003–2012. JAMA: J. Am. Med. Assoc. 313, 1973–1974 (2015).
4. Al, B., Bogan, M., Zengin, S., Sabak, M., Kul, S., Oktay, M. M., … Vuruskan, E.: Effects of Dust Storms and Climatological Factors on Mortality and Morbidity of Cardiovascular Diseases Admitted to ED. Emergency Medicine International, 2018(Dm), 1–7 (2018). http://doi.org/10.1155/2018/3758506
5. Alexander, R., Nugent, C., & Nugent, K.: The Dust Bowl in the US: An Analysis Based on Current Environmental and Clinical Studies. The American Journal of the Medical Sciences, 356(2), 90–96 (2018). http://doi.org/10.1016/J.AMJMS.2018.03.015
6. Anderson HR, Favarato G, Atkinson RW.: Long-term exposure to air pollution and the incidence of asthma: meta-analysis of cohort studies. Air Qual Atmos Health 6:47–56 (2013).
7. Badii, M.H., Guillen, A., & Abreu, J. L.: Tamaño Óptimo de Muestra en Ciencias Sociales y Naturales Optimal Simple Size (OSS) in Social and Natural Sciences, 9(2), 41–51 (2014).
8. Bai, Y., Sun, Q.: Macrophage recruitment in obese adipose tissue. Obes. Rev. 16, 127–136 (2015). http://dx.doi.org/10.1111/obr.12242
9. Barrett, B., Charles, J. W., & Temte, J. L.: Climate change, human health, and epidemiological transition. Preventive Medicine, 70, 69–75 (2015). http://doi.org/10.1016/j.ypmed.2014.11.013
10. Behzad, H., Mineta, K., Gojobori, T., Arabia, S., Arabia, S., Sciences, M., Gojobori, T.: Global Ramifications of Dust and Sandstorm Microbiota. Genome Biology and Evolution, 10(July 2018), 1970–1987 (2018). http://doi.org/10.1093/gbe/evy134/5046809
11. Bernier, S.A., Gill, T.E., Peterson, R.E.: Climatology of dust in the Southern High Plains of Texas. In: Busacca, A. (Ed.), Proceedings of the International Conference on Dust Aerosols, Loess Soils and Global Change, Seattle, October 1998. Washington State University College of Agriculture and Home Economics Miscellaneous Publication, vol. 190, pp. 4–7 (1998).
12. Bhagia L. J.: Non-occupational exposure to silica dust. Indian journal of occupational and environmental medicine, 16(3), 95-100 (2012).
13. Bozlaker, A., Peccia, J., & Chellam, S.: Indoor/Outdoor Relationships and Anthropogenic Elemental Signatures in Airborne PM2.5 at a High School: Impacts of Petroleum Refining Emissions on Lanthanoid Enrichment. Environmental Science & Technology, 51(9), 4851–4859 (2017). https://doi.org/10.1021/acs.est.6b06252
14. Braveman, P. A., Kumanyika, S., Fielding, J., LaVeist, T., Borrell, L. N., Manderscheid, R., & Troutman, A.: Health disparities and health equity: The issue is justice. American Journal of Public Health, 101(SUPPL. 1), 149–155 (2011). http://doi.org/10.2105/AJPH.2010.300062

15. Brodie EL, et al.: Urban aerosols harbor diverse and dynamic bacterial populations. Proc Natl Acad Sci USA. 104(1):299–304 (2007).
16. Brook, R.D., Rajagopalan, S., Pope 3rd, C.A.: Particulate matter air pollution and cardiovascular disease: an update to the scientific statement from the American Heart Association. Circulation 121 (21), 2331–2378 (2010).
17. Brown E. G., Gottlieb Selma, Laybourn R. L.: Dust Storms and Their Possible Effect on Health. Public Health Reports, 50(40), 20 (1935).
18. Calderón-Garcidueñas, L., Kulesza, R. J., Doty, R. L., D'Angiulli, A., & Torres-Jardón, R.: Megacities air pollution problems: Mexico City Metropolitan Area critical issues on the central nervous system pediatric impact. Environmental Research, 137, 157–169 (2015). https://doi.org/10.1016/j.envres.2014.12.012
19. Carvalho-Oliveira, R., Pires-Neto, R. C., Bustillos, J. O., Macchione, M., Dolhnikoff, M., Saldiva, P. H., & Garcia, M. L.: Chemical composition modulates the adverse effects of particles on the mucociliary epithelium. Clinics (Sao Paulo, Brazil), 70(10), 706-13 (2015).
20. Chan Y, Van Nostrand JD, Zhou J, Pointing SB, Farrell RL.: Functional ecology of an antarctic dry valley. Proc Natl Acad Sci USA. 110(22):8990–8995 (2013).
21. Chan, Y., Teng, J. C., Liu, T., Peng, Y., & Chan, Y.: Asian dust storms and diabetes hospitalization: a nationwide population-based study, 1 (2018).
22. Chen, P.S., Tsai, F.T., Lin, C.K., Yang, C.Y., Chan, C.C., Young, C.Y., Lee, C.H.: Ambient influenza and avian influenza virus during dust storm days and background days. Environ. Health Perspective. 118, 1211–1216 (2010).
23. Chiarelli, S. P., Amador Pereira, L. A., Nascimento Saldiva, P. H. do, Ferreira Filho, C., Bueno Garcia, M. L., Ferreira Braga, A. L., & Conceição Martins, L.: The association between air pollution and blood pressure in traffic controllers in Santo André, São Paulo, Brazil. Environmental Research, 111(5), 650–5 (2011). https://doi.org/10.1016/j.envres.2011.04.007
24. Chien, L.C., Yang, C.H., Yu, H.L.: Estimated effects of Asian dust storms on spatiotemporal distributions of clinic visits for respiratory diseases in Taipei children (Taiwan). Environ. Health Perspect. 120, 1215e1220 (2012).
25. Chung, H., Sobsey, M.D.: Comparative survival of indicator viruses and enteric viruses in seawater and sediment. Water Sci. Technol. 27, 425–428 (1993).
26. Colls, J.: Air Pollution: Measurement, Modelling and Mitigation, Second Edition. London: CRC Press (2002).
27. Cooper, L. A., Purnell, T. S., Ibe, C. A., Halbert, J. P., Bone, L. R., Carson, K. A., … Levine, D. M.: Reaching for Health Equity and Social Justice in Baltimore: The Evolution of an Academic-Community Partnership and Conceptual Framework to Address Hypertension Disparities. Ethnicity & Disease, 26(3), 369–78 (2016). http://doi.org/10.18865/ed.26.3.369
28. Cox, C.S.: Stability of Airborne Microbes and Allergens. In: Cox, C.S., Wathes, C.M. (Eds.), Bioaerosols Handbook. Lewis Publishers, London, UK (1995).
29. Despres, V. R., Huffman, J. A., Burrows, S. M., Hoose, C., Safatov, A. S., Buryak, G., Frohlich-Nowoisky, J., Elbert, W., Andreae, M. O., Pöschl, U., and Jaenicke, R.: Primary biological aerosol particles in the atmosphere: a review, Tellus Ser. B, 64, 15598, doi:10.3402/tellusb.v64i0.15598 (2012).

30. Dostert, C., Pétrilli, V., Van Bruggen, R., Steele, C., Mossman, B. T., & Tschopp, J.: Innate immune activation through Nalp3 inflammasome sensing of asbestos and silica. Science, 320(5876), 674–677 (2008). http://doi.org/10.1126/science.1156995
31. Ebrahimi, S. J. A., Ebrahimzadeh, L., Eslami, A., & Bidarpoor, F.: Effects of dust storm events on emergency admissions for cardiovascular and respiratory diseases in Sanandaj, Iran. Journal of Environmental Health Science and Engineering, 12(1), 1–5 (2014). http://doi.org/10.1186/s40201-014-0110-x
32. EPA Homepage. Criteria Air Pollutants. Retrieved from https://www.epa.gov/criteria-air-pollutants/naaqs-table, last accessed 2018/1/9.
33. EPA Homepage, Reference News Release: Oil Refiners to Reduce Air Pollution at Six Refineries Under Settlement with EPA and Department of Justice. Retrieved from https://www.epa.gov/enforcement/reference-news-release-oil-refiners-reduce-air-pollution-six-refineries-under-settlement, last accessed 2018/7/20.
34. EPA b Homepage, Criteria Air Pollutants. Retrieved from https://www.epa.gov/criteria-air-pollutants/naaqs-table, last accessed 2018/1/9).
35. Etemadifar Z, Gholami M, Derikvand P.: UV-resistant bacteria with multiple-stress tolerance isolated from desert areas in Iran. Geomicrobiol J. 33(7):1–598 (2016).
36. Finkel, M. L.: The impact of oil sands on the environment and health. Environmental Science & Health, 3, 52–55 (2018). https://doi.org/10.1016/J.COESH.2018.05.002
37. Franchini, M., & Mannucci, P. M.: Inhibitors of propagation of coagulation (factors VIII, IX and XI): A review of current therapeutic practice. British Journal of Clinical Pharmacology, 72(4), 553–562 (2011). http://doi.org/10.1111/j.1365-2125.2010.03899.x
38. Franzetti A, Gandolfi I, Gaspari E, Ambrosini R, Bestetti G.: Seasonal variability of bacteria in fine and coarse urban air particulate matter. Appl Microbiol Biotechnol. 90(2):745–753 (2011).
39. Fuzzi, S., Baltensperger, U., Carslaw, K., Decesari, S., Denier Van Der Gon, H., Facchini, M. C., … Gilardoni, S.: Particulate matter, air quality and climate: Lessons learned and future needs. Atmospheric Chemistry and Physics, 15(14), 8217–8299 (2015). http://doi.org/10.5194/acp-15-8217-2015
40. Garcia, G. J. M., Schroeter, J. D., & Kimbell, J. S.: Olfactory deposition of inhaled nanoparticles in humans. Inhalation Toxicology, 27(8), 394–403 (2015). http://doi.org/10.3109/08958378.2015.1066904
41. Garcı´a, J. H., Li, W.-W., Arimoto, R., Okrasinski, R., Greenlee, J., Walton, J., … Sage, S.: Characterization and implication of potential fugitive dust sources in the Paso del Norte region. Science of The Total Environment, 325(1), 95–112 (2004). http://doi.org/10.1016/j.scitotenv.2003.11.011
42. Gee, G. C., Walsemann, K. M., & Brondolo, E.: A life course perspective on how racism may be related to health inequities. American Journal of Public Health, 102(5), 967–974 (2012). http://doi.org/10.2105/AJPH.2012.300666
43. Ghio, A. J., & Huang, Y.-C. T.: Exposure to Concentrated Ambient Particles (CAPs): A Review. Inhalation Toxicology, 16(1), 53–59 (2004). http://doi.org/10.1080/08958370490258390
44. Gill, T.E., Stout, J.E., and Peinado, P.: Composition and characteristics of aerosols in the Southern High Plains of Texas, USA. AIP Conference Proceedings 1099: 255- 258 (2009).

45. Ginoux, P., Prospero, J., Gill, T., Hsu, N., and Zhao, M.: Globalscale attribution of anthropogenic and natural dust sources and their emission rates based on modis deep blue aerosol products, Rev. Geophys., 50, RG3005 (2012). http://doi:10.1029/2012RG000388.
46. Global Change Homepage, https://health2016.globalchange.gov/report-guide#figure-90, last accessed 2017/1/6.
47. Griffin, D.W.: Atmospheric movement of microorganisms in clouds of desert dust and implications for human health. Clin. Microbiol. Rev. 20, 459–477 (2007).
48. Grineski, S. E., Herrera, J. M., Bulathsinhala, P., & Staniswalis, J. G.: Is there a Hispanic Health Paradox in sensitivity to air pollution? Hospital admissions for asthma, chronic obstructive pulmonary disease and congestive heart failure associated with NO2 and PM2.5 in El Paso, TX, 2005–2010. Atmospheric Environment, 119, 314–321 (2015). http://doi.org/10.1016/j.atmosenv.2015.08.027
49. Grineski, S. E., Staniswalis, J. G., Bulathsinhala, P., Peng, Y., & Gill, T. E.: Hospital admissions for asthma and acute bronchitis in El Paso, Texas: Do age, sex, and insurance status modify the effects of dust and low wind events? Environmental Research, 111(8), 1148–1155 (2011). http://doi.org/10.1016/j.envres.2011.06.007
50. Gurgueira, S.A., Lawrence, J., Coull, B., Murthy, G., Gonzalez-Flecha, B.: Rapid increases in the steady-state concentration of reactive oxygen species in the lungs and heart after particulate air pollution inhalation. Environ. Health Perspect. 110, 749–755 (2002). http://dx.doi.org/10.1289/ehp.02110749.
51. Halonen, J. I., Blangiardo, M., Toledano, M. B., Fecht, D., Gulliver, J., Anderson, H. R., … Tonne, C.: Long-term exposure to traffic pollution and hospital admissions in London. Environmental Pollution (Barking, Essex: 1987), 208(Pt A), 48–57 (2016). https://doi.org/10.1016/j.envpol.2015.09.051
52. Hansen J, Sato M, Ruedy R, Lo K, Lea DW, Medina-Elizade M.: Global temperature change. Proc Natl Acad Sci USA;103:14288–93 (2006).
53. Heusinkveld, H. J., Wahle, T., Campbell, A., Westerink, R. H. S., Tran, L., Johnston, H., … Schins, R. P. F.: Neurodegenerative and neurological disorders by small inhaled particles. NeuroToxicology, 56, 94–106 (2016). http://doi.org/10.1016/j.neuro.2016.07.007
54. Holliday, V.T.: The Blackwater Draw Formation (Quaternary): a 1.4-plus-m.y. record of aeolian sedimentation and soil formation on the Southern High Plains. Geol. Soc. Am. Bull. 101, 1598–1607 (1989).
55. Hosiokangas, J., Vallius, M., Ruuskanen, J., Mirme, A., Pekkanen, J.: Resus- pended dust episodes as an urban air-quality problem in subarctic regions. Scandinavian Journal of Work and Environmental Health 30, 28–35 (2004).
56. Howard, G., Peace, F., & Howard, V. J.: The contributions of selected diseases to disparities in death rates and years of life lost for racial/ethnic minorities in the United States, 1999-2010. Preventing Chronic Disease, 11, E129 (2014). http://doi.org/10.5888/pcd11.140138
57. Huang M, Wang W, Chan CY, Cheung KC, Man YB, Wang X, et al.: Contamination and risk assessment (based on bioaccessibility via ingestion and inhalation) of metal(loid)s in outdoor and in- door particles from urban centers of Guangzhou, China. Sci Total Environ;479-480:117-124 (2014).
58. Husar RB, et al.: Asian dust events of April 1998. J Geophys Res. 106(D16):18317–18330 (2001).

59. Intergovernmental Panel on Climate Change (IPCC) a: Climate Change 2007: Impacts, Adaptation and Vulnerability. In: Parry, M.L., Canziani, O.F., Palutikof, J.P., van der Linden, P.J., Hanson, C.E. (Eds.), Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK (2007a).
60. Intergovernmental Panel on Climate Change (IPCC) b: Climate change 2007: impacts, adaptation and vulnerability contribution of Working Group II to the Fourth Assess- ment Report of the Intergovernmental Panel on Climate Change. In: Parry ML, Canzani OP, Palutikof JP, et al, editors. Cambridge, New York: Cambridge University Press; 2007
61. Jacob, Daniel J., and Darrel A. Winner. (2009). Effect of climate change on air quality. Atmospheric Environment 43(1): 51-63 (2007b).
62. Kanatani, K. T., Ito, I., Al-Delaimy, W. K., Adachi, Y., Mathews, W. C., Ramsdell, J. W., … Yamamoto, J.: Desert dust exposure is associated with increased risk of asthma hospitalization in children. American Journal of Respiratory and Critical Care Medicine, 182(12), 1475–1481 (2010). http://doi.org/10.1164/rccm.201002-0296OC
63. Kaplan, R. M.: Behavior change and reducing health disparities. Preventive Medicine, 68, 5–10 (2014). http://doi.org/10.1016/j.ypmed.2014.04.014
64. Karagulian, F., Belis, C. A., Dora, C. F. C., Prüss-Ustün, A. M., Bonjour, S., Adair-Rohani, H., & Amann, M.: Contributions to cities' ambient particulate matter (PM): A systematic review of local source contributions at global level. Atmospheric Environment, 120, 475–483 (2015). http://doi.org/10.1016/j.atmosenv.2015.08.087
65. Karanasiou, A., Moreno, N., Moreno, T., Viana, M., de Leeuw, F., and Querol, X.: Health effects from Sahara dust episodes in Europe: Literature review and research gaps, Environment Int., 47, 107–114 (2012). doi:10.1016/j.envint.2012.06.012.
66. Keil, D. E., Buck, B., Goossens, D., McLaurin, B., Murphy, L., Leetham-Spencer, M., … DeWitt, J. C.: Nevada desert dust with heavy metals suppresses IgM antibody production. Toxicology Reports, 5(June 2017), 258–269 (2018). http://doi.org/10.1016/j.toxrep.2018.01.006
67. Keil, D. E., Buck, B., Goossens, D., Teng, Y., Pollard, J., McLaurin, B., … DeWitt, J.: Health effects from exposure to atmospheric mineral dust near Las Vegas, NV, USA. Toxicology Reports, 3, 785–795 (2016). http://doi.org/10.1016/j.toxrep.2016.09.009
68. Keil, D.E., Buck, B., Goossens, D., Teng, Y., Spencer, M., Murphy, L., Pollard, J., Eggers, M., McLaurin, B., Gerads, R., DeWitt, J.: Immunotoxicological and neurotoxicological profile of health effects following subacute exposure to geogenic dust from sand dunes at the Nellis Dunes Recreation Area Las Vegas, NV. Toxicol. Appl. Pharmacol. 2016;291:1–12 (2016).
69. Khan, R. K., & Strand, M. A.: Road dust and its effect on human health: a literature review. Epidemiology and health, 40, e2018013(2018). Doi:10.4178/epih.e2018013
70. Khaniabadi, Y. O., Fanelli, R., De Marco, A., Daryanoosh, S. M., Kloog, I., Hopke, P. K., … Goudarzi, G. (2017). Hospital admissions in Iran for cardiovascular and respiratory diseases attributed to the Middle Eastern Dust storms. Environmental Science and Pollution Research, 24(20), 16860–16868. http://doi.org/10.1007/s11356-017-9298-5
71. Kinge, J. M., Steingrímsdóttir, Ó. A., Strand, B. H., & Kravdal, Ø.: Can socioeconomic factors explain geographic variation in overweight in Norway? SSM - Population Health, 2, 333–340 (2016). http://doi.org/https://doi.org/10.1016/j.ssmph.2016.04.010

72. Kioumourtzoglou, M. A., Schwartz, J. D., Weisskopf, M. G., Melly, S. J., Wang, Y., Dominici, F., & Zanobetti, A.: Long-term PM Exposure and Neurological Hospital Admissions in the Northeastern United States. Environmental Health Perspectives, 124(1), 23–29 (2015). http://doi.org/10.1289/ehp.1408973
73. Kirkland TN, Fierer J.: Coccidioidomycosis: a reemerging infectious disease. Emerg Infect Dis. 2(3):192–199 (1996).
74. Krieger, N.: Living and Dying at the Crossroads: Racism, Embodiment, and Why Theory Is Essential for a Public Health of Consequence. American Journal of Public Health, 106(5), 832–833 (2016). http://doi.org/10.2105/AJPH.2016.303100
75. Lee, J. A., & Gill, T. E.: Multiple causes of wind erosion in the Dust Bowl. Aeolian Research, 19(November 2006), 15–36 (2015). http://doi.org/10.1016/j.aeolia.2015.09.002
76. Lee, J. A., Baddock, M. C., Mbuh, M. J., & Gill, T. E.: Geomorphic and land cover characteristics of aeolian dust sources in West Texas and eastern New Mexico, USA. Aeolian Research, 3(4), 459–466 (2012). http://doi.org/10.1016/j.aeolia.2011.08.001
77. Lee, J. A., Gill, T. E., Mulligan, K. R., Dominguez Acosta, M., & Perez, A. E.: Land use/land cover and point sources of the 15 December 2003 dust storm in southwestern North America. Geomorphology, 105(1–2), 18–27 (2009). https://doi.org/10.1016/j.geomorph.2007.12.016
78. Lee, J., Baddock, M., Mbuh, M., & Gill, T.: Geomorphic and land cover characteristics of aeolian dust sources in West Texas and eastern New Mexico, USA. Aeolian Research (Vol. 3) (2012). http://doi.org/10.1016/j.aeolia.2011.08.001
79. Lee, J.A., Tchakerian, V.P.: Magnitude and frequency of blowing dust on the Southern High Plains of the United States, 1947–1989. Ann. Assoc. Am. Geogr. 85, 684–693 (1995).
80. Li, J., Kandakji, T., Lee, J. A., Tatarko, J., Blackwell, J., Gill, T. E., & Collins, J. D.: Blowing dust and highway safety in the southwestern United States: Characteristics of dust emission "hotspots" and management implications. Science of The Total Environment, 621, 1023–1032 (2018). http://doi.org/10.1016/J.SCITOTENV.2017.10.124
81. Li, R., Kou, X., Geng, H., Xie, J., Tian, J., Cai, Z., & Dong, C.: Mitochondrial damage: an important mechanism of ambient PM2.5 exposure-induced acute heart injury in rats. Journal of Hazardous Materials, 287, 392–401 (2015). https://doi.org/10.1016/j.jhazmat.2015.02.006
82. Li, W.-W., Orquiz, R., Garcia, J. H., Espino, T., Pingitore, N. E., Gardea-Torresdey, J., … Watson, J. G.: Analysis of temporal and spatial dichotomous PM air samples in the El Paso-Cd. Juarez air quality basin. Journal of the Air & Waste Management Association (1995), 51(11), 1551–60 (2001). http://doi.org/10.1080/10473289.2001.10464377
83. Lim, J.Y., & Chun, Y.: The characteristics of Asian dust events in Northeast Asia during the springtime from 1993 to 2004. Global and Planetary Change, 52, 231–247 (2006).
84. Ma, Y., Zhang, H., Zhao, Y., Zhou, J., Yang, S., Zheng, X., & Wang, S.: Short-term effects of air pollution on daily hospital admissions for cardiovascular diseases in western China. Environmental Science and Pollution Research, 24(16), 14071–14079 (2017). http://doi.org/10.1007/s11356-017-8971-z
85. Middleton, N. J: Desert dust hazards: A global review. Aeolian Research, 24, 53–63 (2017). https://doi.org/https://doi.org/10.1016/j.aeolia.2016.12.001
86. Morman, S. A., & Plumlee, G. S.: The role of airborne mineral dusts in human disease. Aeolian Research, 9, 203–212 (2013). http://doi.org/10.1016/j.aeolia.2012.12.001

87. Morman, S.A. and Plumlee, G.S.: Dust and human health. In Mineral Dust (pp. 385-409). Springer, Dordrecht (2014).
88. Nemmar, A., Al-Salam, S., Zia, S., Dhanasekaran, S., Shudadevi, M., & Ali, B. H.: Time-course effects of systemically administered diesel exhaust particles in rats. Toxicology Letters, 194(3), 58–65 (2010). http://doi.org/10.1016/J.TOXLET.2010.02.001
89. Nemmar, A., Hoylaerts, M. F., Hoet, P. H.., Vermylen, J., & Nemery, B.: Size effect of intratracheally instilled particles on pulmonary inflammation and vascular thrombosis. Toxicology and Applied Pharmacology, 186(1), 38–45 (2003). https://doi.org/10.1016/S0041-008X(02)00024-8
90. Nery, L. E., Florencio, R. T., Sandoval, P. R. M., Rodrigues, R. T., Alonso, G., & Mason, G. R.: Additive effects of exposure to silica dust and smoking on pulmonary epithelial permeability: A radioaerosol study with technetium-99m labelled DTPA. Thorax, 48(3), 264–268 (1993). http://doi.org/10.1136/thx.48.3.264
91. Novlan, D. J., Hardiman, M., & Gill, T. E.: A Synoptic Climatology of Blowing Dust Events in El Paso, Texas from 1932-2005. American Meteorological Society J., 3 (2007).
92. O'Neill, L. A. J. and Dunne, A.: The Interleukin-1 Receptor / Toll-Like Receptor Superfamily, (February), 1–18 (2008).
93. Oberdörster, G., Sharp, Z., Atudorei, V., Elder, A., Gelein, R., Kreyling, W., & Cox, C.: Translocation of inhaled ultrafine particles to the brain. Inhalation Toxicology, 16(6–7), 437–445 (2004). https://doi.org/10.1080/08958370490439597
94. Oil Change International Homepage, Refineries, http://refineryreport.org/refineries.php, last accessed 2018/7/5.
95. Olvera, H. A., Kubzansky, L. D., Campen, M. J., & Slavich, G. M.: Neuroscience and Biobehavioral Reviews Early life stress, air pollution, inflammation, and disease: An integrative review and immunologic model of social-environmental adversity and lifespan health. Neuroscience and Biobehavioral Reviews, 92(May), 226–242 (2018). https://doi.org/10.1016/j.neubiorev.2018.06.002
96. Orgill M.M., Sehmel G.A.: Frequency and diurnal variation of dust storms in the contiguous U.S.A. Atmospheric Environment, 10 pp. 813-825 (1976).
97. Prospero, J.M., Ginoux, P., Torres, O., Nicholson, S.E. and Gill, T.E.: Environmental characterization of global sources of atmospheric soil dust identified with the nimbus 7 total ozone mapping spectrometer (toms) absorbing aerosol product. Reviews of Geophysics 40: doi: 10.1029/2000RG000095. issn: 8755-1209 (2002).
98. Prussin A. J., Garcia E. B., Marr L. C.: Total concentrations of virus and bacteria in indoor and outdoor air. Environ Sci Tech Lett. 2(4):84–88 (2015).
99. Reynolds, K., Go, A. S., Leong, T. K., Boudreau, D. M., Cassidy-bushrow, A. E., Fortmann, S. P., … Sidney, S.: Trends in Incidence of Hospitalized Acute Myocardial Infarction in the Cardiovascular Research Network (CVRN). The American Journal of Medicine (2016). http://doi.org/10.1016/j.amjmed.2016.09.014
100. Rivas, Jose A. Jr., Thomas E. Gill, Elizabeth J. Walsh, and Robert L. Wallace.: Characterization of Dust Transported to El Paso, Texas. Abstracts of the 18th Joint Conference on the Applications of Air Pollution Meteorology with the A&WMA, American Meteorological Society Annual Meeting, Atlanta, GA, February 2014, Abstract # 236614 (2014).

101. Rivera Rivera, N. I., Gill, T. E., Gebhart, K. A., Hand, J. L., Bleiweiss, M. P., & Fitzgerald, R. M.: Wind modeling of Chihuahuan Desert dust outbreaks. Atmospheric Environment, 43(2), 347–354 (2009). http://doi.org/10.1016/j.atmosenv.2008.09.069
102. Rivera, N. I. R., Gill, T. E., Bleiweiss, M. P., & Hand, J. L.: Source characteristics of hazardous Chihuahuan Desert dust outbreaks. Atmospheric Environment, 44(20), 2457–2468 (2010). https://doi.org/10.1016/J.ATMOSENV.2010.03.019
103. Rodo X, et al.: Tropospheric winds from northeastern china carry the etiologic agent of Kawasaki disease from its source to japan. Proc Natl Acad Sci USA. 111(22):7952–7957(2014).
104. Rodopoulou, S., Chalbot, M. C., Samoli, E., DuBois, D. W., San Filippo, B. D., & Kavouras, I. G.: Air pollution and hospital emergency room and admissions for cardiovascular and respiratory diseases in Doña Ana County, New Mexico. Environmental Research, 129, 39–46 (2014). http://doi.org/10.1016/j.envres.2013.12.006
105. Schwarze, P.E., Totlandsdal, A.I., Låg, M., Refsnes, M., Holme, J.A., Øvrevik, J.: Inflammation-related effects of diesel engine exhaust particles: studies on lung cells in vitro. Biomed. Res. Int. 2013, 1–13 (2013). http://dx.doi.org/10.1155/2013/685142.
106. Schweitzer, M. D., Calzadilla, A. S., Salamo, O., Sharifi, A., Kumar, N., Holt, G., Mirsaeidi, M.: Lung health in era of climate change and dust storms. Environmental Research, 163(February), 36–42 (2018). http://doi.org/10.1016/j.envres.2018.02.001
107. Shao, Y.: Physics and modelling of wind erosion (2nd edn.). Heidelberg: Springer (2008).
108. Shrey, K., Suchit, A., Deepika, D., Shruti, K., & Vibha, R.: Air pollutants: the key stages in the pathway towards the development of cardiovascular disorders. Environmental Toxicology and Pharmacology, 31(1), 1–9 (2011). http://doi.org/10.1016/j.etap.2010.09.002
109. Song, Z., Wang, J., & Wang, S.: Quantitative classification of northeast Asian dust events. Journal of Geophysical Research, 112(D4), D04211 (2007). http://doi.org/10.1029/2006JD007048
110. Sujaritpong, S., Dear, K., Cope, M., Walsh, S., & Kjellstrom, T.: Quantifying the health impacts of air pollution under a changing climate-a review of approaches and methodology. International Journal of Biometeorology, 58(2), 149–160 (2014). http://doi.org/10.1007/s00484-012-0625-8
111. Sun, J., Fu, J. S., Huang, K., & Gao, Y.: Estimation of future PM2.5- and ozone-related mortality over the continental United States in a changing climate: An application of high-resolution dynamical downscaling technique. Journal of the Air & Waste Management Association, 65(5), 611–623 (2015). http://doi.org/10.1080/10962247.2015.1033068
112. Tang K, et al.: Characterization of atmospheric bioaerosols along the transport pathway of Asian dust during the dust-bioaerosol 2016 campaign. Atmos Chem Phys. 18:7131–7148 (2018). doi: 10.5194/acp-18-7131.
113. Tarhan, C., Ozcan, N. S., & Ozkan, S. P.: The Relationship between Respiratory Systems' Cases and Environmental Urban Factors. Procedia - Social and Behavioral Sciences, 216, 622–631 (2016). http://doi.org/10.1016/j.sbspro.2015.12.040
114. Texas Climate Descriptions Homepage, http://web2.airmail.net/danb1/texas_climate_descriptions.htm, last accessed 2016/2/6.
115. Tili, E., Michaille, J.-J., Wernicke, D., Alder, H., Costinean, S., Volinia, S., & Croce, C. M.: Mutator activity induced by microRNA-155 (miR-155) links inflammation and cancer.

Proceedings of the National Academy of Sciences of the United States of America, 108(12), 4908–13 (2011). http://doi.org/10.1073/pnas.1101795108
116. Tong DQ, Wang JXL, Gill TE, Lei H, Wang BY.: Intensified dust storm activity and valley fever infection in the southwestern United States. Geophys Res Lett. 44(9):4304–4312 (2017).
117. Tonne, C., Halonen, J. I., Beevers, S. D., Dajnak, D., Gulliver, J., Kelly, F. J., … Anderson, H. R.: Long-term traffic air and noise pollution in relation to mortality and hospital readmission among myocardial infarction survivors. International Journal of Hygiene and Environmental Health, 219(1), 72–78 (2016). https://doi.org/10.1016/j.ijheh.2015.09.003
118.
119. Touloumi, G., Atkinson, R., Le Tertre, A., Samoli, E., Schwartz, J., Schindler, C., et al.: Analysis of health outcome time series data in epidemiological studies. Environmetrics 15, 101–117 (2004).
120. Van Pelt, R. S., & Zobeck, T. M.: Chemical constituents of fugitive dust. Environmental Monitoring and Assessment, 130(1–3), 3–16 (2007). http://doi.org/10.1007/s10661-006-9446-8
121. Vineis, P., Foraster, F., Hoek, G., Lippsett, M.: Outdoor air pollution and lung cancer: recent epidemiological evidence. Int. J. Cancer 111, 647e652 (2004).
122. Wang Y, et al.: Effects of dust storm events on weekly clinic visits related to pulmonary tuberculosis disease in Minqin, China. Atmos Environ. 127:205–212 (2016).
123. Weil T, et al.: Legal immigrants: invasion of alien microbial communities during winter occurring desert dust storms. Microbiome 5(1):32 (2017).
124. Weintraub, D., Xie, S., Karlawish, J., & Siderowf, A.: Differences in depression symptoms in patients with Alzheimer's and Parkinson's diseases: evidence from the 15-item Geriatric Depression Scale (GDS-15). International journal of geriatric psychiatry, 22(10), 1025-30 (2007).
125. Wolf, K., Schneider, A., Breitner, S., Meisinger, C., Heier, M., Cyrys, J., Peters, A.: Associations between short-term exposure to particulate matter and ultrafine particles and myocardial infarction in Augsburg, Germany. International Journal of Hygiene and Environmental Health, 218(6), 535–42 (2015). https://doi.org/10.1016/j.ijheh.2015.05.002
126. Wu, S., Ni, Y., Li, H., Pan, L., Yang, D., Baccarelli, A. A., … Guo, X.: Short-term exposure to high ambient air pollution increases airway inflammation and respiratory symptoms in chronic obstructive pulmonary disease patients in Beijing, China. Environ Int, 94, 76–82 (2016). https://doi.org/10.1016/j.envint.2016.05.004
127. Yu, H. L., Chien, L. C., & Yang, C. H.: Asian dust storm elevates children's respiratory health risks: A spatiotemporal analysis of children's clinic visits across Taipei (Taiwan). PLoS ONE, 7(7), 1–9 (2012). http://doi.org/10.1371/journal.pone.0041317
128. Zablocki O, Adriaenssens EM, Cowan D.: Diversity and ecology of viruses in hyperarid desert soils. Appl Environ Microbiol. 82(3):770–777 (2016).
129. Zhang, X., Zhao, L., Tong, Q. D., Wu, G., Dan, M., & Teng, B.: A Systematic Review of Global Desert Dust and Associated Human Health Effects. Atmosphere (2016). http://doi.org/10.3390/atmos7120158

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

Estrella D. Molina-Herrera
University of Texas at El Paso, USA

Luis Ernesto Cervera-Gómez
El Colegio de Chihuahua, Mexico

Carlos Herrera
University of Texas at El Paso, USA & El Paso VA Health Care System, USA

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.

DOI: 10.4018/978-1-5225-8131-4.ch003

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

Estrella Molina-Herrera[1], Alberto Ochoa[2], Luis Ernesto Cervera-Gomez[3] & Carlos Herrera[4]
UTEP[1], Juarez City University[2], Colech[3], EPVAHCS[4]
México[1,3]
United States[2,4]

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 $V = \{V0, \mathrm{V1}, ..., \mathrm{Vn}\}$, and arcs are represented by $A = \{(vi,\ vj\ )\ |\ i\ = j\}$ The distances associated with each arc are represented by the variable Cij measured by the Euclidean distance. The objective functions of the problem [7] are:

$$minZ = \text{All the defined arcs } CijXij \tag{1}$$

Decision variables are as follows:

- Xij : action to move from node i to node j 0 indicates that there is no displacement and 1 indicates that yes there is movement.
- Cij : 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 $(i, j)\ Xij$ = (external output from node j) + k All the defined arcs

$$(j,k)\ Xjk \tag{2}$$

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:

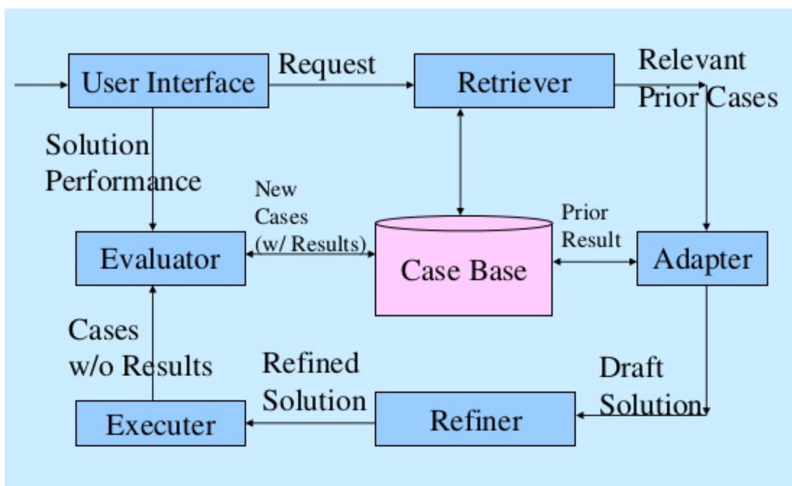

Figure 3. 1 Basic structure of an RBC system according to Shiu et al. (2004).

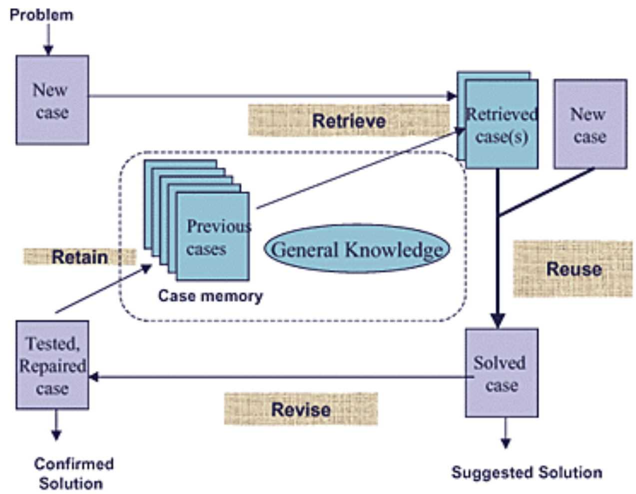

Figure 3. 2 Life cycle of the RBC according to Fornells (2009).

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).

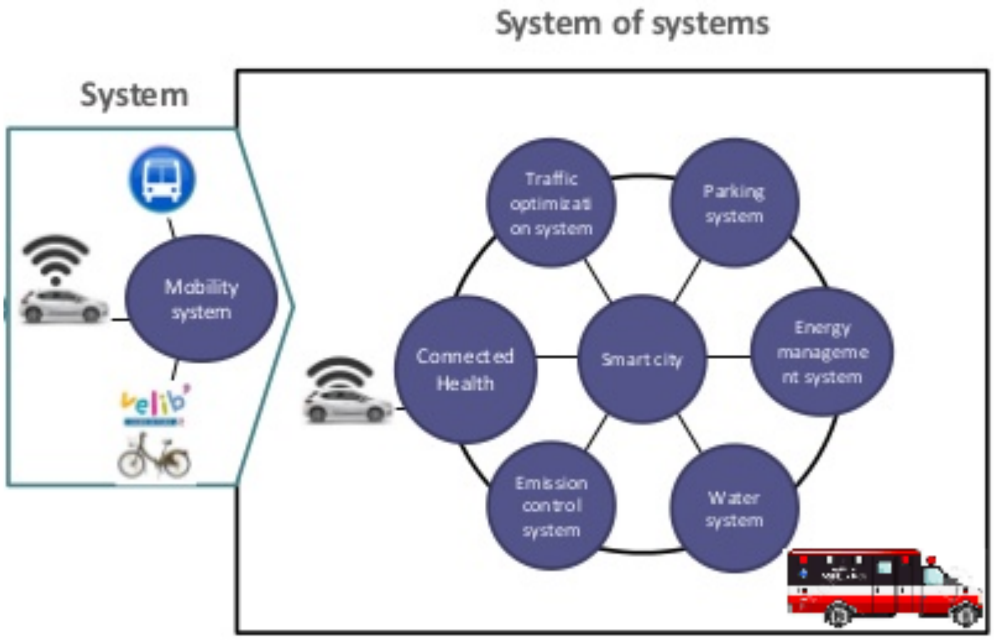

Figure 3. 3 An ambulance in a transport model in a Smart City.

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:

$$dij = \alpha daij + \beta dbij + \gamma dcij + \cdots \tag{3}$$

Let tij (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
```

$$\tau ij\ (t + n) \varrho \cdot \tau ij\ (t) + \Delta \tau ij \tag{4}$$

where ϱ is a coefficient that represents the evaporation of trail between $\Delta\tau ij = m$.

$$k = 1 \Delta\tau\ kij \tag{5}$$

$$dij = adaij + \beta dbij + \gamma dcij + \ldots \quad (3)$$

The coefficient ϱ 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, tij (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 hlist, 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 hlist is used to compute the ant's current solution (i.e., the movement cost of the path followed by the ant). The hlist is then emptied, and the ant is free to choose again,

$$\tau ij\ (t + n)\ \varrho \tau ij\ (t) + \Delta \tau ij \quad (4)$$

$$k = 1 \Delta \tau kij \quad (5)$$

$$\eta ij = 1/dij \quad (6)$$

We call visibility hij the quantity 1/dij . 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 kth ant as

$$pk\ ij\ = \tau ij\ \ (t)\alpha \cdot \eta ij\beta\ k \in allowed\ \ k\tau ik\ (t)\alpha \cdot \eta ik\beta \quad (7)$$

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).

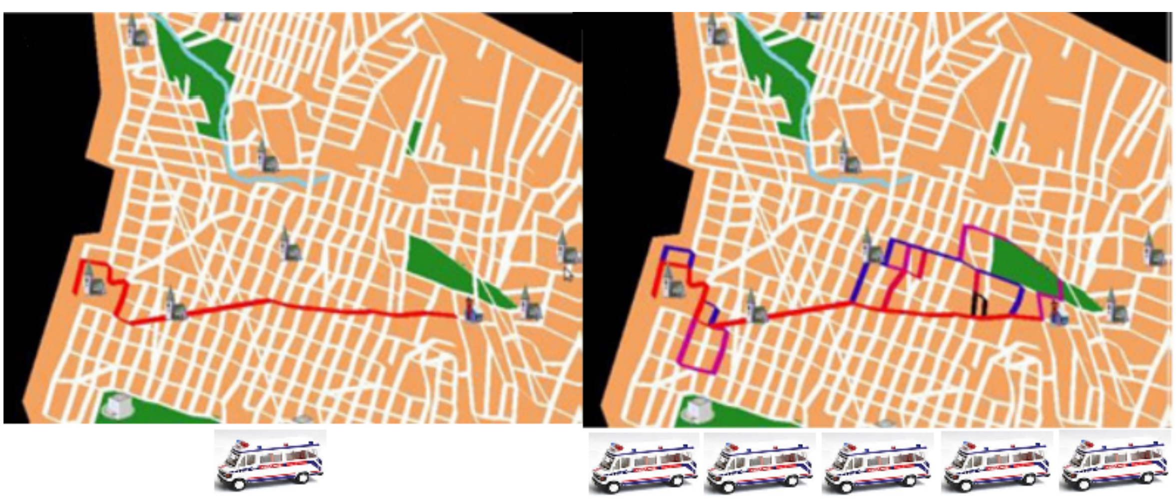

Figure 3. 4 Drawing of a single route (left) and drawing of five routes (right).

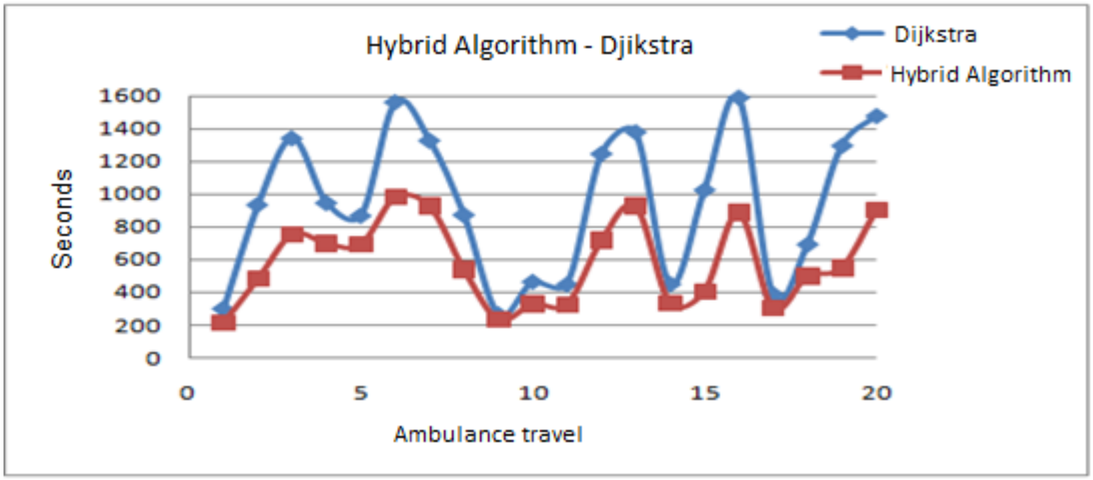

Figure 3. 5 ACO and Case-based Reasoning and Dijkstra comparison.

Table 3. 1 Result for each ambulance travel from the houses of the patients to a Hospital in El Paso.

#	Origin	Destination	Dijkstra	Hybrid Algorithm
1	945	759	222	212
2	614	759	464	507
3	903	759	755	841
4	941	759	732	698
5	1044	759	693	709
6	1202	759	984	1093
7	1094	759	953	927
8	1057	759	538	538
9	1418	759	231	231
10	170	759	338	328
11	526	759	347	324
12	462	759	718	718
13	846	759	859	1030
14	524	759	359	333
15	809	759	365	406
16	1107	759	886	1011
17	698	759	302	302
18	1062	759	517	499
19	1342	759	519	564
20	1199	759	885	984

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.

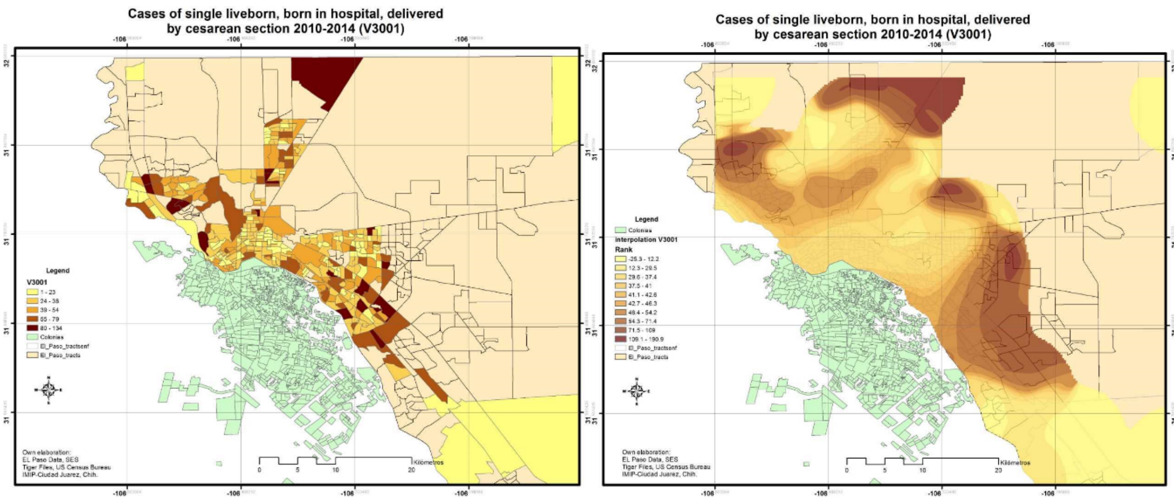

Figure 3. 6 Incidence of a specific sickness in Neighborhoods of El Paso, and a Kriging Model of incidence of this sickness in the future with the necessity of more ambulances to transport more patients during a Dust storm.

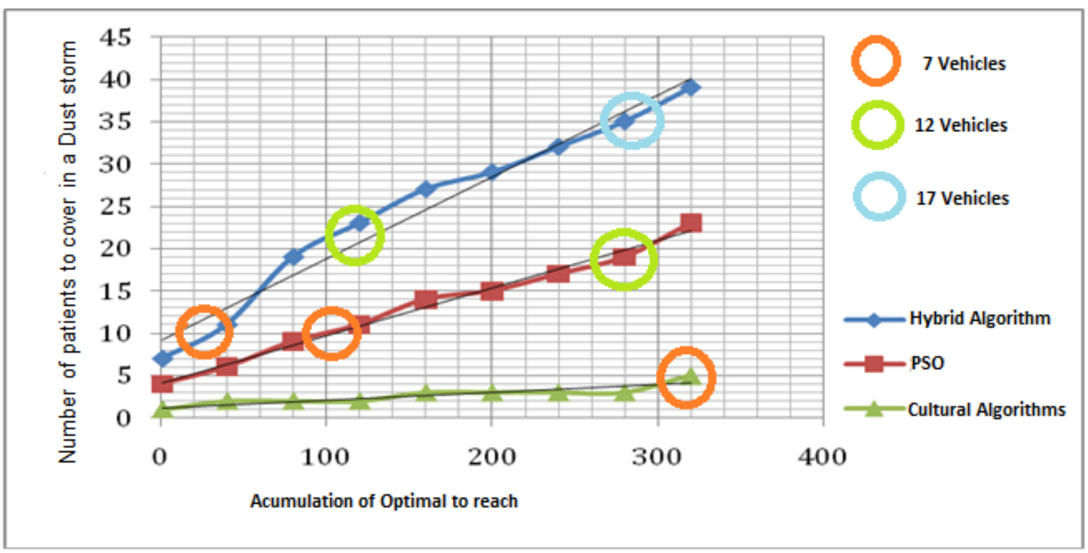

Figure 3. 7 Comparative analysis of a Hybrid Algorithm, a PSO and a Cultural Algorithm for an instance of three emergencies associated with a Dust Storm at the same time, when we consider its performance on the basis of Table 3.1.

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

[1] L. Barcos, V. M. Rodrıguez, M. J. Alvarez, and F. Robust e, Routing design for less-than-truckload motor carriers using ant colony techniques. Business Economics Working Papers, Series 14. Universidad Carlos III de Madrid. Departamento de Economıa de la Empresa, paper number wb043814, 2004.

[2] J. E. Bell and P. R. McMullen, Ant colony optimization techniques for the vehicle routing problem, Advanced Engineering Informatics, 18 (2004), 41–48.

[3] M. Birattari, P. Pellegrini, and M. Dorigo, On the invariance of ant system, in Ant Colony Optimization and Swarm Intelligence, 5th International Workshop, ANTS 2006, LNCS 4150, M. Dorigo, L. M. Gambardella, M. Birattari, A. Martinoli, R. Poli, and T. Stutzle, eds., Springer-Verlag, Berlin, 2006, 215– ¨ 223.

[4] M. Dorigo, M. Birattari, and T. Stutzle, ¨ Ant colony optimization – artificial ants as a computational intelligence technique, IEEE Computational Intelligence Magazine, 1 (2006), 28–39. [5] M. Dorigo and G. Di Caro, The ant colony optimization metaheuristic, in New Ideas in Optimization, D. Corne, M. Dorigo, and F. Glover, eds., McGraw Hill, London, UK, 1999, 11–32.

[6] K. Ghoseiri and B. Nadjari, An ant colony optimization algorithm for the bi-objective shortest path problem, Applied Soft Computing, 10 (2010), 1237–1246.

[7] R. P. Grimaldi, Matematicas Discretas y Combinatoria, Editorial Addison Wesley, Mexico, 5th ed., 1995.

[8] L. Hong, An improved LNS algorithm for real-time vehicle routing problem with time windows, Comput Oper Res, 39 (2012), 151–163.

[9] R. Johnsonbaugh, Matematicas Discretas, Grupo Editorial Pearson Education, Mexico, 6 ed., (2005).

[10] S. R. Kolavali and S. Bhatnagar, Ant colony optimization algorithms for shortest path problems, in Network Control and Optimization, vol. 5425 of Lectures Notes in Computer Science, Springer-Verlag, Berlin, 2009.

[11] H. Lei, G. Laporte, and B. Guo, The capacitated vehicle routing problem with stochastic demands and time windows, Comput Oper Res, 38 (2011), 1775–1783.

[12] J. C. Ponce, Diseno de un Modelo de Optimizacion de Colonias de Hormigas Aplicado al Problema del Clique Maximo. Tesis Doctoral. Universidad Autonoma de Aguascalientes, Doctorado en Ciencias de la Computacion, Aguascalientes, Mexico, 2010.

[13] H. A. Taha, Investigacion de Operaciones, Editorial Alfaomega, Mexico, 5th ed., 2008. No. de paginas 960.

[14] W. Xiong, L. Wang, and C. Yan, Binary ant colony evolutionary algorithm, Int J Inform Technol, 12 (2006), 10–20.

[15] F. Yu, Y. Li, and T. Wu, A temporal ant colony optimization approach to the shortest path problem in dynamic scale-free networks, Physica A: Statistical Mechanics and its Applications, 389 (2010), 629–636.

[16] S. R. Mohammad, Mei Y., Hamilton M., Salim F. D. CAPRA: A contour-based accessible path routing algorithm, Information Sciences, Volumes 385–386, (2017), Pages 157-173.

[17] Talarico L., Meisel F., Sörensen K., Ambulance routing for disaster response with patient groups, Computers & Operations Research, Volume 56, (2015), Pages 120-133.

[18] van Barneveld T.C., Bhulai S., van der Mei R.D., The effect of ambulance relocations on the performance of ambulance service providers, European Journal of Operational Research, Volume 252, Issue 1, (2016), Pages 257-269.

[19] ŞİMŞEK A., KARA R., Using swarm intelligence algorithms to detect influential individuals for influence maximization in social networks, Expert Systems with Applications, Volume 114, (2018), Pages 224-236.

[20] Behbahani, Morteza & Saghaee, Abbas & Noorossana, Rassoul. (2012). A case-based reasoning system development for statistical process control: Case representation and retrieval. Computers & Industrial Engineering. 63. 1107–1117. 10.1016/j.cie.2012.07.007.

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

Estrella Molina-Herrera[1], Thomas E. Gill[1], Gabriel Ibarra-Mejia[1], Alberto Ochoa-Zezzatti[2], Soyoung Jeon[3]

[1] University of Texas at El Paso, El Paso, TX 79968, USA
[2] The Autonomous University of Ciudad Juarez, Cd Juárez, Chihuahua. 32310, Mexico
[3] New Mexico State University

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/m^3 increments in maximum PM_{10} 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 $\mu g/m^3$ 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, &

Li et al., 2018). 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/m^3 on February 20, 2013 (Rivas et al., 2014), and maximum hourly PM_{10} of 4739.3μg/m^3 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/m^3 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/m^3 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, Osteoarthrosis, 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 PM_{10} 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.

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.

Neurodegenerative Diseases (ND)	
Parkinson	3330, 3320, 3321
Alzheimer	3310, 29411, 33119, 3312, 3313, 3315, 33182, 33189, 33181, 33182, 3319
Huntington	3334, 3331, 3332, 3335, 3336, 33382, 33383, 33385, 33390, 33391, 33392, 33394, 33399
Mental Illness (MI)	
Depression	311, 2980, 29620, 29621, 29622, 29623, 29624, 29630, 29631, 29632, 29633, 29634
Anxiety	29384, 30000, 30001, 30002, 30009, 30921, 30924, 30928
Valley Fever (VF)	
Valley Fever	1140, 1142, 1143, 1144, 1145
Asthma	
Asthma	49300, 49301, 49302, 49310, 49311, 49312, 49320, 49321, 49322, 49381, 49382, 49390, 49391, 49392
Coronary Atherosclerosis	
Coronary Atherosclerosis	41400, 41401, 41402, 41404, 41405, 41406, 4148, 4149
Associated Diseases (ADs) with most frequent hospitalizations	
Births	V3001, V3000, 66411, 66401, 65421, 650, 64421, 66331, 65971, 64891, 64511, 65811
Respiratory System	49121, 486, 49392, 51884, 46611, 46619, 51881, 49391
Circulatory System	42731, 41071, 43491, 41401, 4280, 42823, 42833
Digestive System	5770, 56211, 5609, 5589, 57400, 5409
Genitourinary System	5849, 5990, 6262, 59080
Encounter for antineoplastic chemotherapy	V5789, V5811
Unspecified septicemia	0389
Other chest pain	78659, 78650
Dehydration	27651
Cellulitis and abscess of leg	6826, 6823
Osteoarthrosis	71536, 71535, 71516, 72210
Diabetes mellitus	25013
Mental Disorders	29680, 29689, 29633, 29630, 29570, 29690, 29650, 29623, 29620

Category Codes from the International Classification of Diseases, Ninth Revision (ICD)-9			
Code Range	Diagnosis	Code Range	Diagnosis
1: 001-139	Infectious and parasitic diseases	10: 580-629	Diseases of the genitourinary system
2: 140-239	Neoplasms	11: 630-679	Complications of pregnancy, childbirth, and the puerperium
3: 240-279	Endocrine, nutritional and metabolic diseases, and immunity disorders	12: 680-709	Diseases of the skin and subcutaneous tissue
4: 280-289	Diseases of the blood and blood-forming organs	13: 710-739	Diseases of the musculoskeletal system and connective tissue
5: 290-319	Mental disorders (Depressed mood, dementia)	14: 740-759	Congenital anomalies
6: 320-389	Diseases of the nervous system and sense organs (Alzheimer's disease)	15: 760-779	Certain conditions originating in the perinatal period
7: 390-459	Diseases of the circulatory system	16: 780-799	Symptoms, signs, and ill-defined conditions
8: 460-519	Diseases of the respiratory system	17: 800-999	Injury and poisoning
9: 520-579	Diseases of the digestive system	18: V01-V91	Aftercare services or therapies (except mental disorders-group 5 & births-group 11)

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 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 $>100\mu g/m^3$ 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.

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

Where E[Yτ] is the expected value of the Poisson distributed variable, Yτ, indicating the daily admissions count on a day τ for each diagnosis with Var(Y τ); α refers to the intercept of the hospital admissions; β_i refers to the coefficients associated with the pollutant and windspeed (i = 1, 2); γ_j the coefficients associated with other covariates (j = 1, 2, ⋯, 11); $PM_{10_{\tau,\tau+7}}$is the cross-basis matrices of PM_{10} maximum hourly level on day τ with lags up to seven days; $WS_{\tau,\tau+7}$ is the cross-basis matrices of wind speed maximum hourly average level on day τ with lags up to seven days; $Temp_{\tau,\tau+3}$ is the cross-basis matrices of average temperature by two lag strata, 0 and 1-3; $Humd_{\tau,\tau+5}$ is the cross-basis matrices of average humidity on day τ with lags up to five days; DE

is the maximum hourly average PM_{10} of $150\mu g/m^3$ and/or the maximum hourly average wind speed of 10 mph maximum hourly average on day τ; DE_{7d} 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(·) 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 $100\mu g/m^3$ increase in PM_{10} or 10mph increase in wind speed) based on the final selected regression model. The β_1 represents the log of expected counts of hospital admission per $100\mu g/m^3$ 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.

$$Log\ E[Y\tau\ ] = \alpha + (Selected\ variables\ in\ Aim\ 3)\ + \cdots + \delta_1\ Age + \delta_2\ Income + \delta_3\ Education$$

Where E[Yτ] is the expected value of the Poisson distributed variable, Yτ, indicating the daily admissions on a day τ for each diagnosis; α refers to the intercept of the hospital admissions; δ_k refers to the coefficients of the demographic and SES variables (k = 1, 2, 3); *Age* is average age of the CBG cohort; *Income* is average income of Hispanic in CBG; and *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.

Diseases	Total	Min	Max	Average	SD
Valley Fever	44	0	1	0.02	0.15
ND	435	0	4	0.24	0.51
Coronary Atherosclerosis	2,974	0	16	1.63	1.60
Asthma	3030	0	18	1.66	1.59
MI	4107	0	14	2.25	1.73
Aftercare services (ICD-9 C.18)	8,258	0	28	4.52	3.21
Injury and poisoning (ICD-9 C.17)	21,398	0	63	11.72	4.89
Respiratory System (ICD-9 C.8)	23,401	0	96	12.82	8.93
Circulatory system (ICD-9 C.7)	31,345	0	68	17.17	7.03
AD	133,848	0	320	73.30	29.76
All ICD-9	299,804	0	632	61.51	164.19
Diabetes mellitus	1,069	0	6	0.59	0.81
Cellulitis and abscess of leg	2,128	0	7	1.17	1.15
Dehydration	2,254	0	11	1.23	1.29
Osteoarthrosis	3,324	0	12	1.82	2.15
Other chest pain	3,667	0	18	2.01	1.60
Unspecified septicemia	3,834	0	9	2.10	1.52
Mental Disorders	3,882	0	31	2.13	1.88
Encounter for antineoplastic chemotherapy	7,056	0	18	3.86	2.84
Genitourinary System	8,772	0	24	4.80	2.67
Digestive System	10,067	0	22	5.51	2.94
Circulatory System	12,361	0	34	6.77	3.37
Respiratory System	14,914	0	75	8.17	6.45
Births	60,520	0	192	33.14	17.13

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, 2010-1014.

	Max Wind Speed	Max PM_{10}	Max Temp	Avg Temp	Max RH	Avg RH
Min	2.5	7.8	14.8	10.8	8.7	4.40
Max	34.2	4739.3	105.9	94.4	100	89.3
Average	12.38	94.14	77.64	67.24	51.29	33.39
SD	5.01	178.11	15.68	15.46	20.87	16.14

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 $\mu g/m^3$ increase of PM_{10}). 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 PM_{10}); Septicemia during the day of DE (RR of 1.019: 1.00005–1.039 per 100 $\mu g/m^3$ increase of PM_{10}); all ICD-9 Category hospitalizations during the day of DE (RR of 1.005: 1.0002–1.009 per 100 $\mu g/m^3$ increase of PM_{10}) (Table 4.4).

The significant Poisson regression results, that is the analysis with the maximum PM_{10} 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 PM_{10}, 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 PM_{10}, 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 PM_{10}, 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.

Data	Variable	Diseases	Lag day	Higher risk		
				RR	**lower.95CI**	**upper.95CI**
Diseases with high hospitalization frequency	PM_{10}	ND	7	1.051	1.009	1.095
		AD	0	1.005	1.001	1.009
			1	1.004	1.001	1.007
			2	1.003	1.001	1.006
		Chemotherapy	7	1.023	1.005	1.04
		Births	3	1.005	1.00006	1.01
		Septicemia	0	1.019	1.00005	1.039
	WS	Genitourinary	0	1.056	1.001	1.114
		Valley Fever	6	1.468	1.014	2.126
		Coronary Atherosclerosis	0	1.117	1.025	1.216
ICD9 Category	PM_{10}	Circulatory system	0, 7	1.011	1.003	1.018
		Aftercare services	7	1.018	1.001	1.034
		All ICD-9	0	1.005	1.00022	1.009
		Injury and poisoning	7	1.011	1.002	1.019
		Respiratory system	6	1.007	1.001	1.014
	WS	Injury and poisoning	0	1.037	1.002	1.074

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.

Data	Hospitalizations Coef. after SES factors are added	Estimate	Std. Error	t value	P-value
Diseases with high hospitalization frequency	**Chemotherapy**				
	Average Income	1.75E-06	0.000	1.909	0.056
	AD				
	Age	-0.005	0.001	-7.175	0.000*
	Births				
	Age &	0.018	0.003	5.411	0.000*
	Med. Education	-0.016	0.005	-3.038	0.002*
ICD9 Category	**Circulatory system**				
	Medium Education	-0.020	0.006	-3.350	0.001*
	Injury and poisoning				
	Ave. Income &	4.26E-06	0.000	4.058	0.000*
	Med. Education	-0.029	0.006	-4.909	0.000*
	Aftercare services				
	Ave. Income &	2.15E-06	0.000	2.327	0.020*
	Med. Education	-0.023	0.006	-3.600	0.000*
	Respiratory system				
	Age &	-0.002	0.001	-3.113	0.002*
	Med. Education	-0.013	0.006	-2.075	0.038*
	All ICD-9				
	Age	-0.006	0.001	-8.547	0.000*

*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 $\mu g/m^3$ 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 $\mu g/m^3$ 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 $\mu g/m^3$ 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/m^3 increase of max PM_{10}). 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/m^3 increase of max PM_{10}), and from 1.018 to 1.017 on LD 7 (95% CI= [1.003–1.032] per 100 μg/m^3 increase of max PM_{10}), 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/m^3 increase of max PM_{10}). 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/m^3 increase of max PM_{10}) 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/m^3 increase of max PM_{10}) (see Figure 4.11).

Table 4. 6 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.

Data	Hospitalizations RR after SES factors are added	Lag day	Hospitalizations RR	lower.95CI	upper.95CI
Diseases with high hospitalization frequency	**Chemotherapy**	7	1.023	1.005	1.040
	Average Income		1.020	1.005	1.036
	AD	0	1.005	1.001	1.009
	Age		1.001	0.997	1.005
	Births	3	1.005	1.00006	1.010
	Age &	2	1.005	1.0002	1.010
	Med. Education	3	1.005	1.0002	1.010
ICD9 Category	**Circulatory system**	7	1.011	1.003	1.018
	Medium Education		1.010	1.003	1.017
	Injury and poisoning	7	1.011	1.002	1.019
	Ave. Income & Med. Education		1.009	1.001	1.017
	Aftercare services	7	1.018	1.001	1.034
	Ave. Income & Med. Education		1.017	1.003	1.032
	Respiratory system	6	1.0065	0.999	1.013
	Age & Med. Education		1.007	1.001	1.014
	All ICD-9	0	1.005	1.0002	1.009
			1.000	0.998	1.003
	Age	1	1.003	1.001	1.005
		2	1.003	1.001	1.004

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.

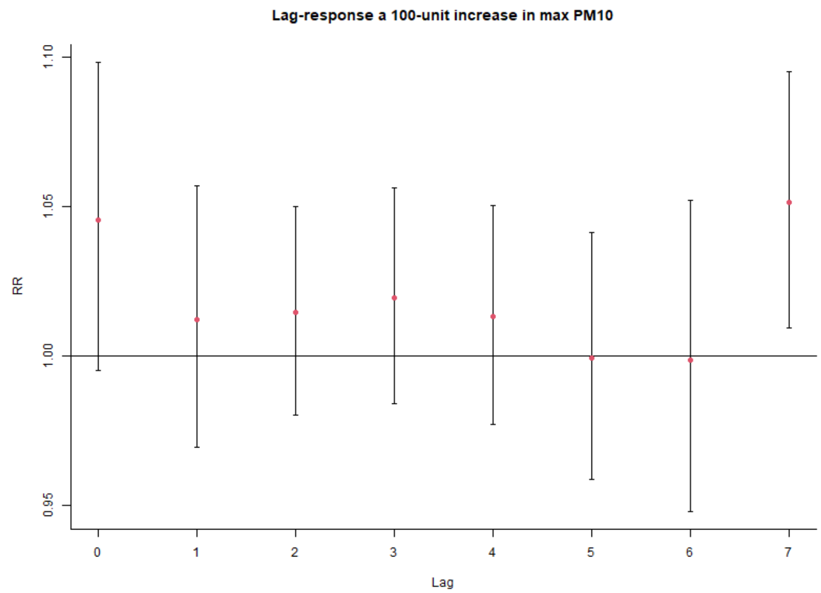

Figure 4. 1 Risk Ratio of ND per Change of Maximum PM_{10}.

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% Cl= [1.001–1.009] for day 0; RR of 1.004: 95% Cl= [1.001–1.007] for day 1 after a DE; RR of 1.003: 95% Cl= [1.001–1.005] for day 2 after a DE per 100 μg/m^3 increase of max PM_{10}) (Figure 4.2).

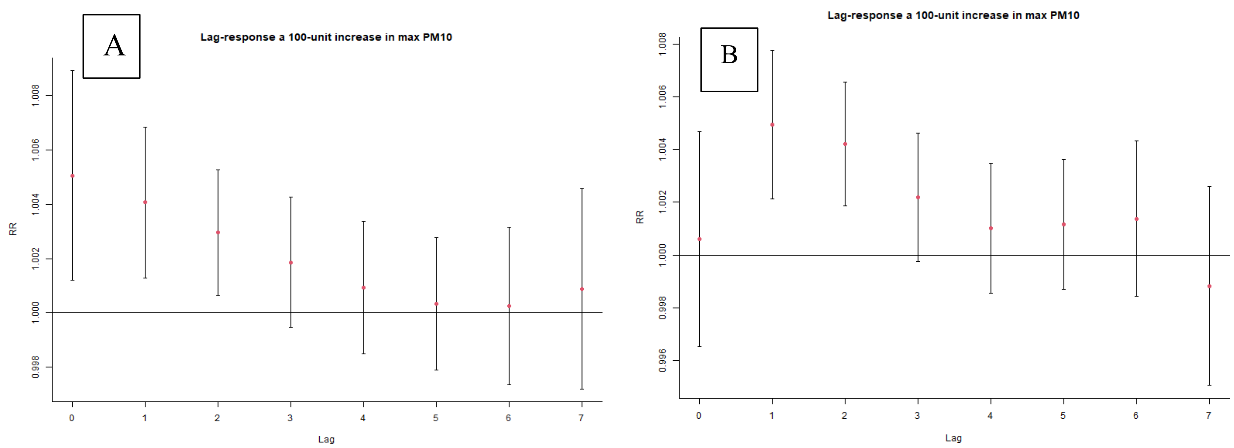

Figure 4. 2 (A)Risk Ratio of AD per Change of Maximum PM_{10} and (B) after Age was analyzed. Income and medium education were not significant (P-values>0.1).

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% Cl= [1.005–1.040] per 100 μg/m^3 increase of max PM_{10}) (Figure 4.3).

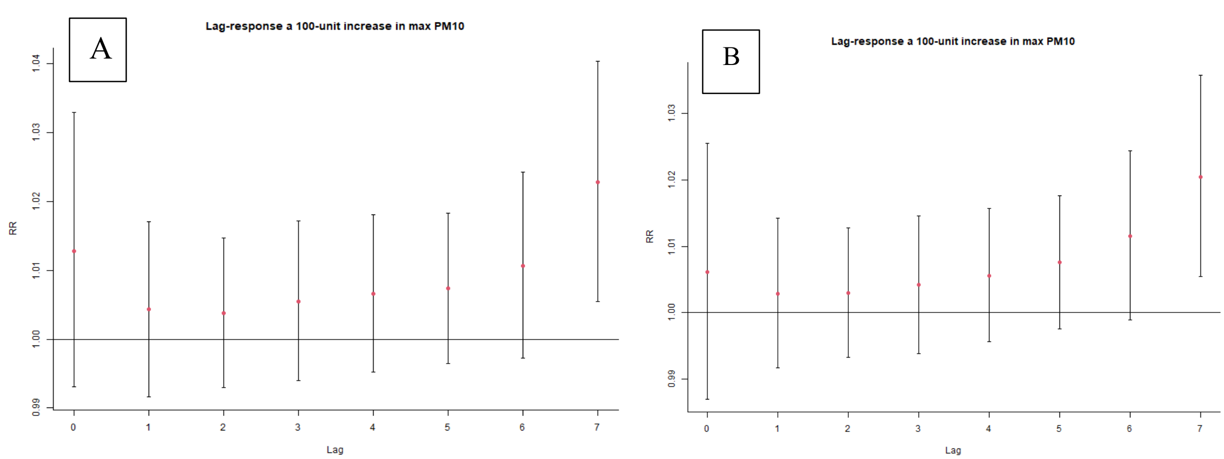

Figure 4. 3 (A)Risk Ratio of antineoplastic chemotherapy and rehabilitation procedure per Change of Maximum PM10 and (B) after Income was analyzed. Medium education was not significant (p=0.17).

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.

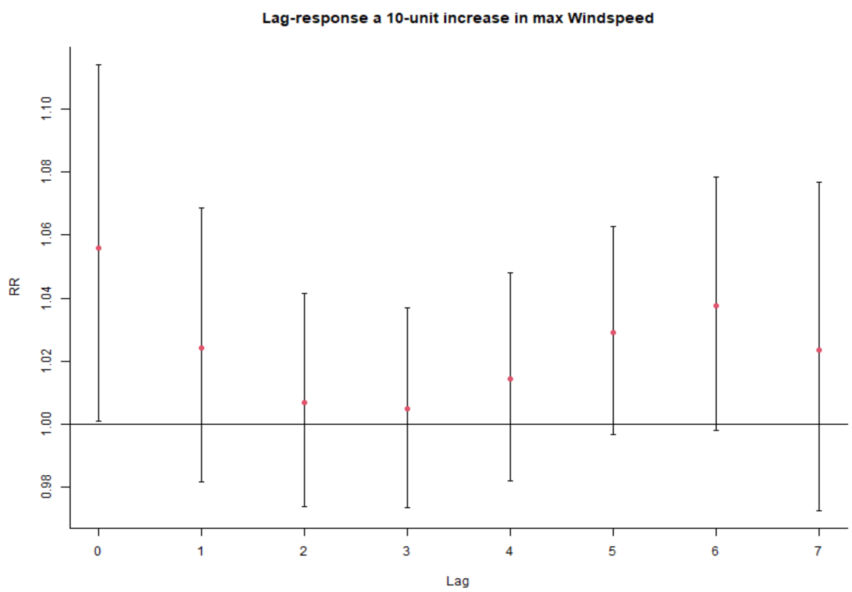

Figure 4. 4 Risk Ratio of Genitourinary System diseases per Change of Maximum PM_{10}.

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% Cl= [1.014–2.126] per 10 mph increase of max wind speed) for the day 6th after a DE (Figure 4.5).

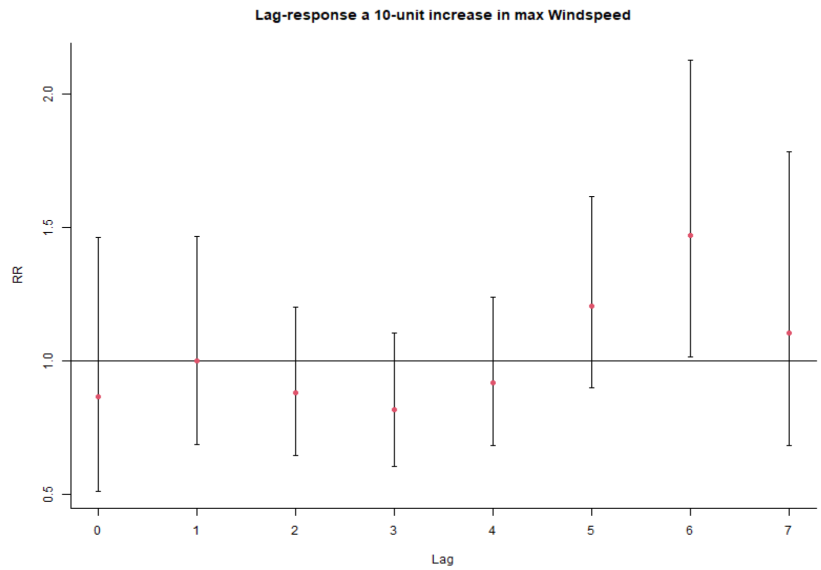

Figure 4. 5 Risk Ratio of Valley Fever per Change of Maximum Windspeed. Demographic factors were not significantly associated.

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% Cl= [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% Cl= [0.904-0.997] per 10 mph increase of max wind speed) (Figure 4.6). Demographic factors were not significantly associated.

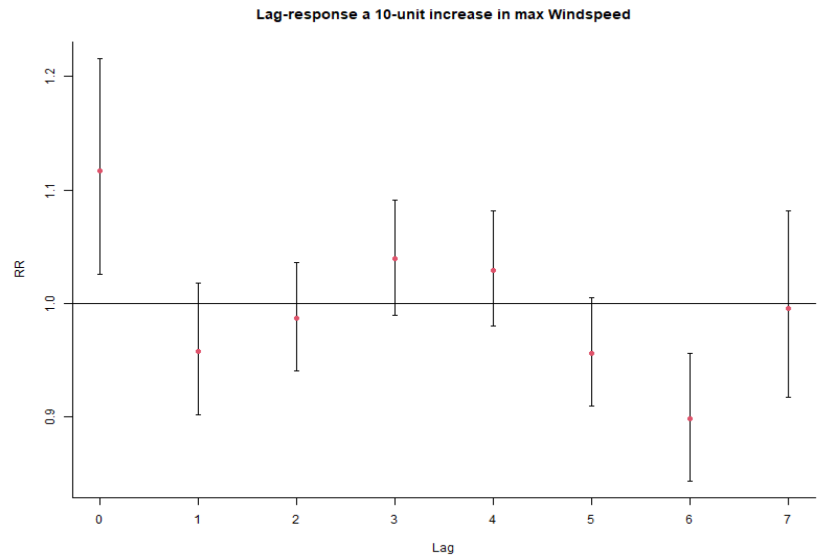

Figure 4. 6 Risk Ratio of Coronary Atherosclerosis diseases per Change of Maximum Wind speed.

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).

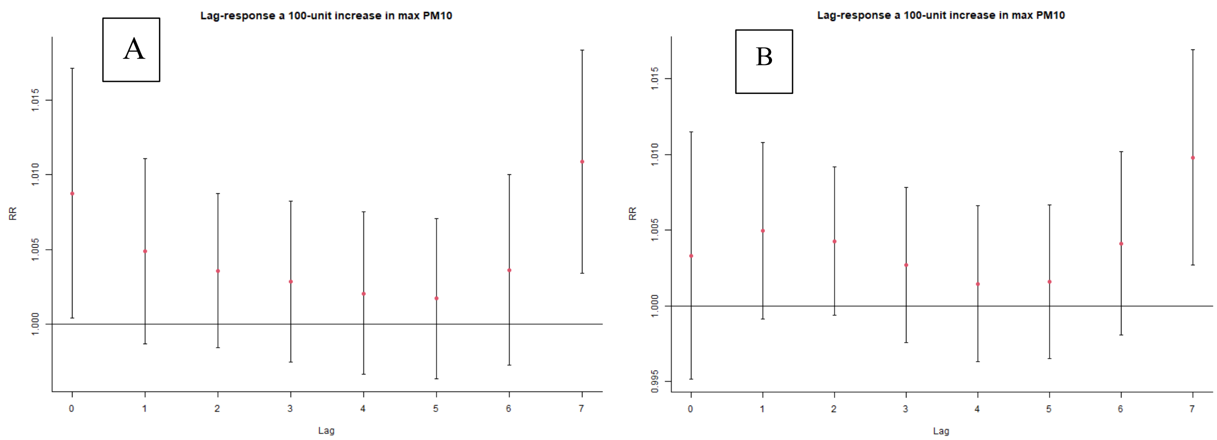

Figure 4. 7 (A) Risk Ratio of Circulatory system diseases (ICD-9 Category 7) per Change of Maximum PM_{10} and (B) after medium education was analyzed. Income was not significant (p=0.41).

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% Cl= [1.002–1.019] per 100 µg/m^3 increase of max PM_{10}) (Figure 4.8).

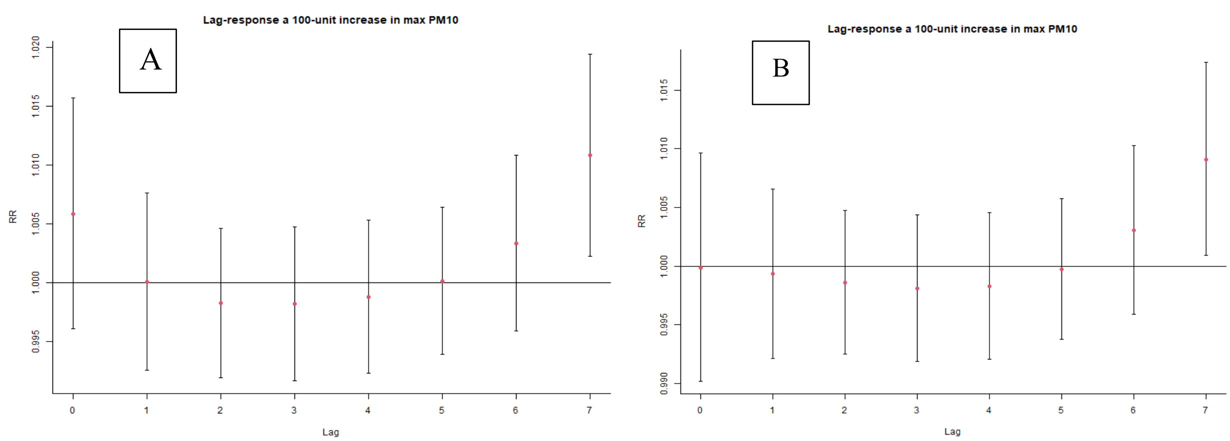

Figure 4. 8 (A)Risk Ratio of Injury and poisoning (ICD-9 Category 17) per Change of Maximum PM_{10} and (B) after income and medium education was analyzed.

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% Cl= [1.001–1.034] per 100 μg/m^3 increase of max PM_{10}) (Figure 4.9).

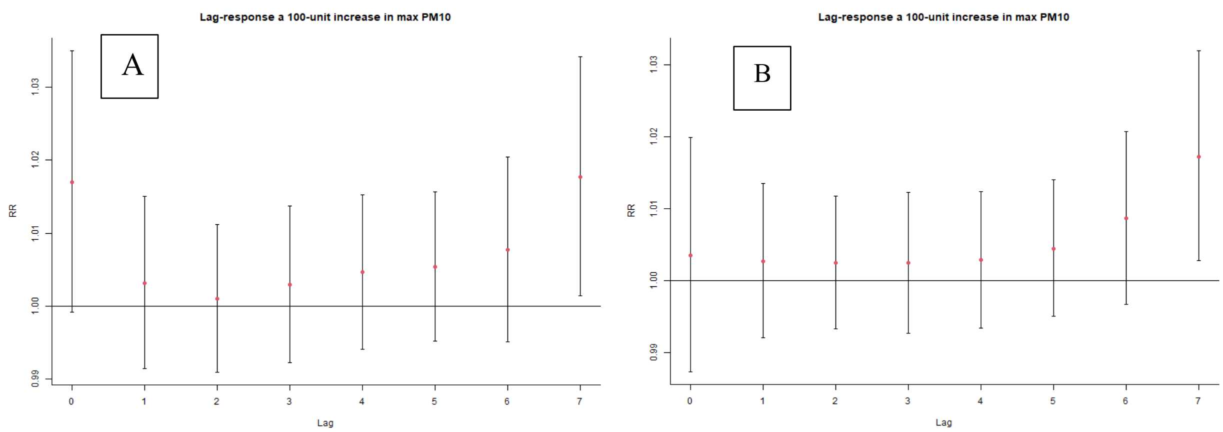

Figure 4. 9(A)Risk Ratio of Aftercare services or therapies (ICD-9 Category 18) per Change of Maximum PM_{10} and (B) after income and medium education was analyzed.

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).

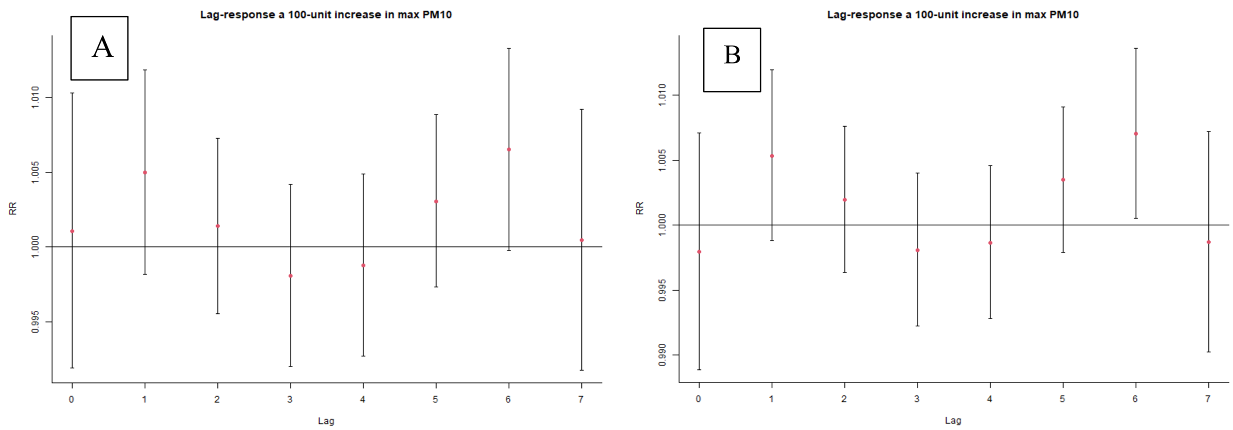

Figure 4. 10 (A) Risk Ratio of respiratory system diseases (ICD-9 Category 18) per Change of Maximum PM_{10} and (B) after age and medium education was analyzed.

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).

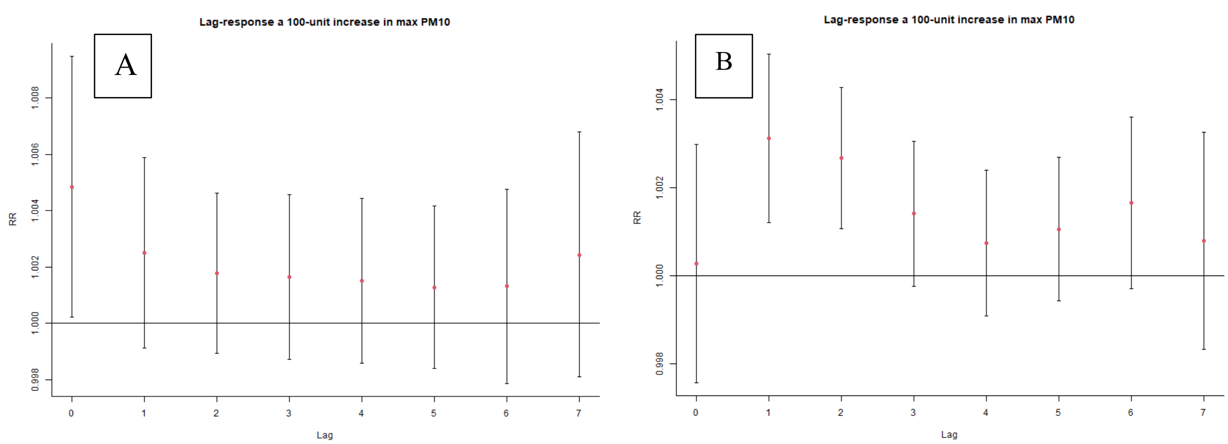

Figure 4. 11 (A) Risk Ratio of All ICD-9 Category admissions per Change of Maximum PM_{10} and (B) after age was analyzed.

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).

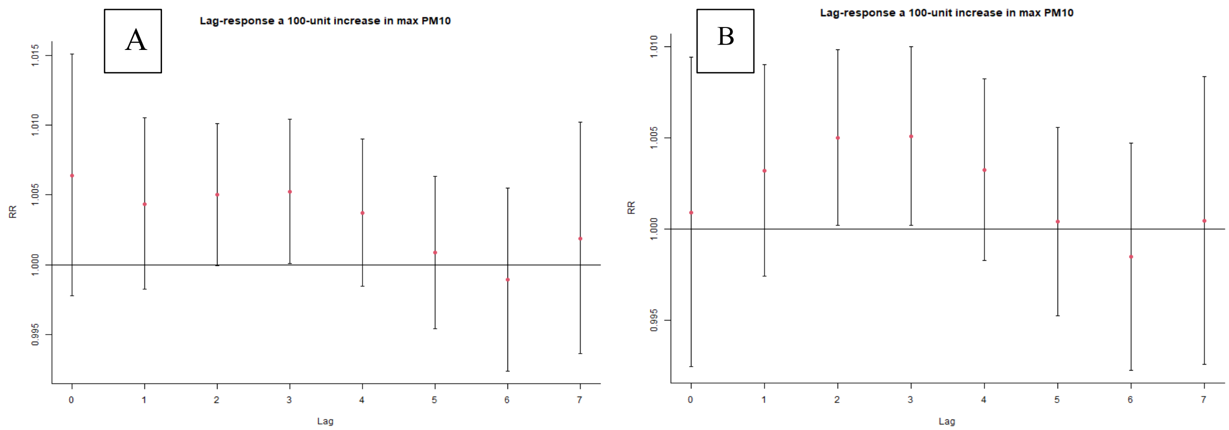

Figure 4. 12 (A) Risk Ratio of births admissions per Change of Maximum PM_{10} and (B) after age and medium education was analyzed.

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.

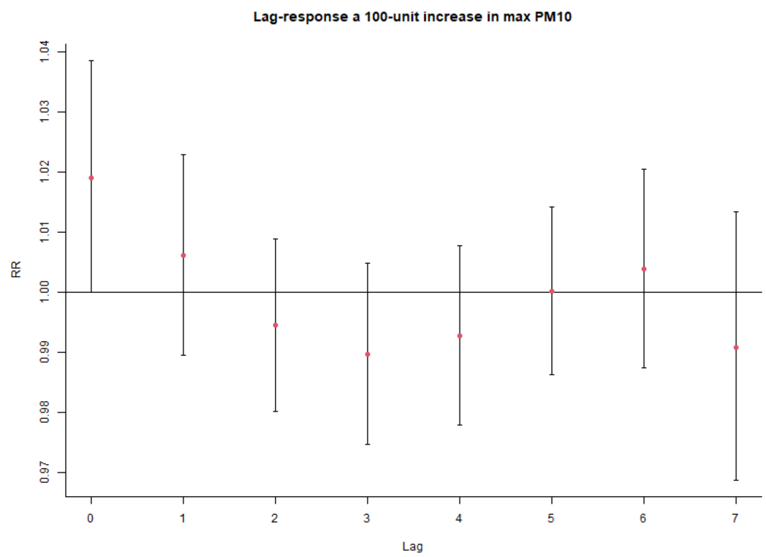

Figure 4. 13 Risk Ratio of Septicemia admissions per Change of Maximum PM_{10}.

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 $\mu g/m^3$ 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, Osteoarthrosis, 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 PM_{10} levels >150 μg/m^3, 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/m^3 increase of PM_{10}). In this analysis, births were borderline significantly associated with a 100-unit increase in maximum PM_{10} at day 3 after a DE (RR of 1.005: 1.0002–1.010 per 100 μg/m^3 increase of PM_{10}) (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% Cl= [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 μg/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 μg/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 μg/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, Osteoarthrosis, 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 100$\mu g/m^3$ increase in PM_{10} 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.

Acknowledgements

We express our appreciation to Hector Olvera, Karin Ardon-Dryer and Tarek Kandakji for useful discussions. The first author acknowledges support from the Environmental Science and Engineering program at the University of Texas at El Paso and a dissertation scholarship provided by the Society of Hispanic Professional Engineers (SHPE). Institutional Review Board approval was obtained from the University of Texas at El Paso, with permit #00001224.

References

Ahmed, C., Yang, J., Chen, J. Y., Jiang, H., Cullen, C., Karavalakis, G., and Lin, Y. H. (2020). Toxicological responses in human airway epithelial cells (BEAS-2B) exposed to particulate matter emissions from gasoline fuels with varying aromatic and ethanol levels. Science of the Total Environment, 706, 135732. https://doi.org/10.1016/j.scitotenv.2019.135732

Arizona Department of Health Services (ADHS). (2016). Valley Fever 2016 Annual Report, 24. https://www.azdhs.gov/documents/preparedness/epidemiology-disease-control/valley-fever/reports/valley-fever-2016.pdf

Baddock, M. C., Gill, T. E., Bullard, J. E., Dominguez Acosta, M., and Rivera Rivera, N. I. (2011), Geomorphology of the Chihuahuan desert based on potential dust emissions, Journal of Maps, 7, 249–259.

Block, M. L., Elder, A., Auten, R. L., Bilbo, S. D., Chen, H., Chen, J. C., and Wright, R. J. (2012). The outdoor air pollution and brain health workshop. NeuroToxicology, 33(5), 972–984. https://doi.org/10.1016/j.neuro.2012.08.014

Braithwaite, I., Zhang, S., Kirkbride, J.B., Osborn, D.P.J., and Hayes, J.F. (2019). Air Pollution (Particulate Matter) Exposure and Associations with Depression, Anxiety, Bipolar, Psychosis and Suicide Risk: A Systematic Review and Meta-Analysis. Environmental Health Perspectives. 127(12):126002. DOI: 10.1289/EHP4595.

Bushnell, J., McLeod, D., and Dowell, A. (2005). Do patients want to disclose psychological problems to GPs? Family Practice 22, 631–637.

Carinanos, P., Galan, C., Alcazar, P., and Dominguez, E., 2007. Analysis of solid particulate matter suspended in the air of Cordoba, southwestern Spain. The Annals of Agricultural and Environmental Medicine, 14, 219–224.

Centers for Disease Control and Prevention (CDC) (2013), Increase in reported coccidioidomycosis—United States, 1998–2011, MMWR (Morbidity and Mortality Weekly Report), 62(12), 217.

Centers for Disease Control and Prevention (CDC) (2021, July 16). Symptoms of Valley Fever (Coccidioidomycosis) https://www.cdc.gov/fungal/diseases/coccidioidomycosis/symptoms.html

Centers for Disease Control and Prevention (CDC) (2021, June 14). Valley Fever (Coccidioidomycosis) Statistics https://www.cdc.gov/fungal/diseases/coccidioidomycosis/statistics.html

Chan, Y. S., Teng, J. C. Y., Liu, T. C., and Peng, Y. I. (2018). Asian dust storms and diabetes hospitalization: a nationwide population-based study. Air Quality, Atmosphere and Health, 11(10), 1243–1250. http://doi.org/10.1007/s11869-018-0623-z

Chen, Y.H., Lin, R.R., and Tao, Q.Q. (2021). The role of P2X7R in neuroinflammation and implications in Alzheimer's disease. Life Sciences, 271, 119187. https://doi.org/10.1016/j.lfs.2021.119187.

Cheng, F.J., Lee, K.H., Lee, C.W., and Hsu, P.C. (2019). Association between Particulate Matter Air Pollution and Hospital Emergency Room Visits for Pneumonia with Septicemia: A Retrospective Analysis. Aerosol and Air Quality Research, 19(2), 345–354. https://doi.org/10.4209/aaqr.2018.08.0285

Chien, L.C., Yang, C.H., and Yu, H.L. (2012). Estimated effects of Asian dust storms on spatiotemporal distributions of clinic visits for respiratory diseases in Taipei children (Taiwan). Environmental Health Perspectives, 120, 1215-1220.

Crotti, A., and Glass, C.K. (2015). The choreography of neuroinflammation in Huntington's disease. Trends in Immunology, 36(6), 364–373. https://doi.org/10.1016/j.it.2015.04.007

Dadvand, P., Basagaña, X., Figueras, F., Amoly, E., Tobias, A., De Nazelle, A., and Nieuwenhuijsen, M.J. (2011). Saharan dust episodes and pregnancy. Journal of Environmental Monitoring, 13(11), 3222–3228. https://doi.org/10.1039/c1em10579e

Fasola, S., Maio, S., Baldacci, S., La Grutta, S., Ferrante, G., Forastiere, F., Stafoggia, M., Gariazzo, C., Silibello, C., Carlino, G., Viegi, G., and the BEEP Collaborative Group. (2021). Short-Term Effects of Air Pollution on Cardiovascular Hospitalizations in the Pisan Longitudinal Study. International Journal of Environmental Research and Public Health, 18(3), 1164. https://doi.org/10.3390/ijerph18031164

Ghio, A.J. (2014). Particle exposures and infections. Infection 42, 459–467. https://doi.org/10.1007/s15010-014-0592-6.

Grineski, S.E., Staniswalis, J.G., Bulathsinhala, P., Peng, Y., and Gill, T.E. (2011). Hospital admissions for asthma and acute bronchitis in El Paso, Texas: Do age, sex, and insurance status modify the effects of dust and low wind events? Environmental Research, 111(8), 1148–1155. http://doi.org/10.1016/j.envres.2011.06.007

Healthline Media. (2021, July 16). Everything you need to know about inflammation https://www.medicalnewstoday.com/articles/248423

Heusinkveld, H. J., Wahle, T., Campbell, A., Westerink, R. H. S., Tran, L., Johnston, H., and Schins, R. P. F. (2016). Neurodegenerative and neurological disorders by small inhaled particles. NeuroToxicology, 56, 94–106. http://doi.org/10.1016/j.neuro.2016.07.007

Hofflinger, A., and Boso, A. (2021). Another one breathes the dust. The relation between severe air pollution episodes and school attendance in southern Chile, Local Environment, 26:2, 252-263, DOI: 10.1080/13549839.2021.1886065

Hudson, C. G. (2005). Socioeconomic status and mental illness: tests of the social causation and selection hypotheses. The American Journal of Orthopsychiatry, 75(1), 3–18. https://doi.org/10.1037/0002-9432.75.1.3

Kang, L., Ling-Ling, C., Shin-Mei, H., Cheng-Yu, T., Dean, W., Chia-Jung, C., Hsiao-Chi, C., and Wen-Te, L. (2021). Association of short-term exposure to air pollution with depression in patients with sleep-related breathing disorders. Science of the Total Environment. 786, 147291. https://doi.org/10.1016/j.scitotenv.2021.147291.

Kavouras, I. G., DuBois, D. W., Nikolich, G., Corral Avittia, A. Y., and Etyemezian, V. (2016). Particulate dust emission factors from unpaved roads in the U.S.-Mexico border semi-arid region. Journal of Arid Environments, 124, 189–192. https://doi.org/10.1016/j.jaridenv.2015.07.015

Kiaei, M. (2013). New hopes and challenges for treatment of neurodegenerative disorders: great opportunities for young neuroscientists. Basic and Clinical Neuroscience, 4(1), 3–4.

Kim, E.A. (2017). Particulate Matter (Fine Particle) and Urologic Diseases. International Neurology Journal, 21(3), 155–162. https://doi.org/10.5213/inj.1734954.477

Kioumourtzoglou, M. A., Schwartz, J. D., Weisskopf, M. G., Melly, S. J., Wang, Y., Dominici, F., and Zanobetti, A. (2015). Long-term PM Exposure and Neurological Hospital Admissions in the Northeastern United States. Environmental Health Perspectives, 124(1), 23–29. http://doi.org/10.1289/ehp.1408973

Lee, H. and Kim, H. (2016). Short-term exposure to PM10 and emergency admissions for Parkinson's disease in Seoul, Korea. ISEE Conference Abstracts. 2016. 10.1289/isee.2016.4309.

Lee, J.A., Gill, T.E., Mulligan, K.R., Dominguez Acosta, M., and Perez, A.E. (2009). Land use/land cover and point sources of the 15 December 2003 dust storm in southwestern North America. Geomorphology, 105(1–2), 18–27. https://doi.org/10.1016/j.geomorph.2007.12.016

Lee, P.C., Talbott, E.O., Roberts, J.M., Catov, J.M., Sharma, R.K., and Ritz, B. (2011). Particulate air pollution exposure and C-reactive protein during early pregnancy. Epidemiology (Cambridge, Mass.), 22(4), 524–531. https://doi.org/10.1097/EDE.0b013e31821c6c58

Li, J., Kandakji, T., Lee, J.A., Tatarko, J., Blackwell, J., Gill, T.E., and Collins, J.D. (2018). Blowing dust and highway safety in the southwestern United States: Characteristics of dust emission "hotspots" and management implications. Science of The Total Environment, 621, 1023–1032. http://doi.org/10.1016/J.SCITOTENV.2017.10.124

Li, W.-W., Orquiz, R., Garcia, J. H., Espino, T., Pingitore, N. E., Gardea-Torresdey, J., and Watson, J. G. (2001). Analysis of temporal and spatial dichotomous PM air samples in the El Paso-Cd. Juarez air quality basin. Journal of the Air & Waste Management Association, 51(11), 1551–1560. https://doi.org/10.1080/10473289.2001.10464377

Lim, J.Y., and Chun, Y. (2006). The characteristics of Asian dust events in Northeast Asia during the springtime from 1993 to 2004. Global and Planetary Change, 52,231–247.

McKesson Corporation. (2013). clinical decision support. DM-IQC-FS-0813

Medical Research Council. (2021, May 29). What is neurodegeneration, dementia, and mental health? https://mrc.ukri.org/successes/investing-for-impact/priority-challenges/neurodegeneration-dementia-and-mental-health/what-is-neurodegeneration-dementia-and-mental-health/

Meng, Z., and Lu, B. (2007). Dust events as a risk factor for daily hospitalization for respiratory and cardiovascular diseases in Minqin, China. Atmospheric Environment, 41(33), 7048–7058. https://doi.org/10.1016/j.atmosenv.2007.05.006

Middleton, N., and Kang, U. (2017). Sand and dust storms: Impact mitigation. Sustainability (Switzerland), 9(6), 1–22. https://doi.org/10.3390/su9061053

Mikati, I., Benson, A.F., Luben, T.J., Sacks, J.D., and Richmond-Bryant, J. (2018). Disparities in distribution of particulate matter emission sources by race and poverty status. American Journal of Public Health, 108(4), 480–485. https://doi.org/10.2105/AJPH.2017.304297

Mohan Kumar S.M., Campbell A., Block M., and Veronesi, B. (2008). Particulate matter, oxidative stress and neurotoxicity. Neurotoxicology 29(3):479-488. https://doi: 10.1016/j.neuro.2007.12.004.

Morman, S.A. and Plumlee, G.S. (2014). Dust and human health. In: Knippertz, P., and Stuut, J.B.W., Mineral Dust a Key Player in The Earth System, Springer, pp. 385-409.

National Collaborating Centre for Mental Health, & Health (NCCMH). (2011). Common Mental Health Disorders Identification and Pathways. National Collaborating Centre for Mental Health. http://guidance.nice.org.uk/CG90

Newcomer, L. N., Gould, B., Page, R. D., Donelan, S. A., and Perkins, M. (2014). Changing physician incentives for affordable, quality cancer care: results of an episode payment model. Journal of Oncology Practice, 10(5), 322–326. https://doi.org/10.1200/JOP.2014.001488

Novlan, D.J., Hardiman, M., and Gill, T.E. (2007). A Synoptic Climatology of Blowing Dust Events in El Paso, Texas from 1932-2005. Preprints, American Meteorological Society Annual Meeting, 16th Symposium on Applied Climatology, J.3. 12

Olvera, H.A., Kubzansky, L.D., Campen, M.J., and Slavich, G.M. (2018). Early life stress, air pollution, inflammation, and disease: An integrative review and immunologic model of social-environmental adversity and lifespan health. Neuroscience and Biobehavioral Reviews, 92, 226–242. https://doi.org/10.1016/j.neubiorev.2018.06.002

Pampel, F. C., Krueger, P. M., and Denney, J. T. (2010). Socioeconomic Disparities in Health Behaviors. Annual Review of Sociology, 36, 349–370. https://doi.org/10.1146/annurev.soc.012809.102529

Peixoto, M.S., de Oliveira Galvão, M.F., and Batistuzzo de Medeiros, S.R. (2017). Cell death pathways of particulate matter toxicity. Chemosphere, 188, 32–48. https://doi.org/10.1016/j.chemosphere.2017.08.076.

Perl, D. P., Olanow, C. W., and Calne, D. (1998). Alzheimer's disease and Parkinson's disease: distinct entities or extremes of a spectrum of neurodegeneration?. Annals of Neurology, 44(3 Suppl 1), S19–S31. https://doi.org/10.1002/ana.410440705

Prospero, J.M., Ginoux, P., Torres, O., Nicholson, S.E., and Gill, T.E. (2002). Environmental characterization of global sources of atmospheric soil dust identified with the nimbus 7 total ozone mapping spectrometer (TOMS) absorbing aerosol product. Reviews of Geophysics 40 (1), 1002. doi:10.1029/2000RG000095

Rivas, J.A. (2019). Dust Storms and The Dispersal of Aquatic Invertebrates in The Chihuahuan Desert Ecoregion. Dissertation, Biological Sciences, University of Texas at El Paso. ETD Collection for University of Texas, El Paso. AAI27667795. https://scholarworks.utep.edu/dissertations/AAI27667795

Rivas, J.A., Gill T.E., Walsh E.J., and Wallace R.L., (2014). Characterization of Dust Transported to El Paso, Texas. Abstracts of the 18th Joint Conference on the Applications of Air

Pollution Meteorology with the A&WMA, American Meteorological Society Annual Meeting, Atlanta, GA, Abstract # 236614.

Rivera Rivera, N.I., Gill, T.E., Gebhart, K.A., Hand, J.L., Bleiweiss, M.P., and Fitzgerald, R.M. (2009). Wind modeling of Chihuahuan Desert dust outbreaks. Atmospheric Environment, 43(2), 347–354. https://doi.org/10.1016/J.ATMOSENV.2008.09.069

Rivera Rivera, N.I., Gill, T.E., Bleiweiss, M.P., and Hand, J.L. (2010). Source characteristics of hazardous Chihuahuan Desert dust outbreaks. Atmospheric Environment, 44(20), 2457–2468. https://doi.org/10.1016/J.ATMOSENV.2010.03.019

Rodopoulou, S., Chalbot, M.C., Samoli, E., DuBois, D.W., San Filippo, B.D., and Kavouras, I.G. (2014). Air pollution and hospital emergency room and admissions for cardiovascular and respiratory diseases in Doña Ana County, New Mexico. Environmental Research, 129, 39–46. https://doi.org/10.1016/j.envres.2013.12.006

Santos, U. P., Terra-Filho, M., Lin, C. A., Pereira, L. A., Vieira, T. C., Saldiva, P. H., and Braga, A. L. (2008). Cardiac arrhythmia emergency room visits and environmental air pollution in Sao Paulo, Brazil. Journal of Epidemiology and Community Health, 62(3), 267–272.

Sareen, J., Afifi, T. O., McMillan, K. A., and Asmundson, G. J. (2011). Relationship between household income and mental disorders: findings from a population-based longitudinal study. Archives of General Psychiatry, 68(4), 419–427. https://doi.org/10.1001/archgenpsychiatry.2011.15

Saydoff, J., Sheng, J. G., Hu, Z., Gonzalez, A., Liu, L., Brenneman, D., Garcia, R.A., Cardin, S., and von Borstel, R.W. (2005). PN401 decreases neurodegeneration in models of Alzheimer's, Huntington's and Parkinson's disease, neuroinflammation, excitotoxicity and has antiepileptic activity. Alzheimer's & Dementia, 1(1) (Supplement), S68.

Schweitzer, M.D., Calzadilla, A.S., Salamo, O., Sharifi, A., Kumar, N., Holt, G., Campos, M., and Mirsaeidi, M. (2018). Lung health in era of climate change and dust storms. Environmental Research, 163, 36–42. https://doi.org/10.1016/j.envres.2018.02.001

Staniswalis, J.G., Parks, N.J., Bader, J.O. and Muñoz-Maldonado, Y. (2005). Temporal Analysis of Airborne Particulate Matter Reveals a Dose-Rate Effect on Mortality in El Paso: Indications of Differential Toxicity for Different Particle Mixtures, Journal of the Air & Waste Management Association, 55:7, 893-902, DOI: 10.1080/10473289.2005.10464696

Szyszkowicz, M., Rowe, B. H., and Colman, I. (2009). Air pollution and daily emergency department visits for depression. International Journal of Occupational Medicine and Environmental Health, 22(4), 355–362. https://doi.org/10.2478/v10001-009-0031-6

Takagi, H., Hari, Y., Nakashima, K., Kuno, T., and Ando, T. (2020). Wind and coronary artery disease. European Journal of Preventive Cardiology, 27(19), 2259–2263. https://doi.org/10.1177/2047487319885195

Tarhan, C., Ozcan, N. S., and Ozkan, S. P. (2016). The Relationship between Respiratory Systems' Cases and Environmental Urban Factors. Procedia - Social and Behavioral Sciences, 216, 622–631. http://doi.org/10.1016/j.sbspro.2015.12.040

Texas Commission on Environmental Quality (TCEQ). (2021, June 16). El Paso: Particulate Matter History. https://www.tceq.texas.gov/airquality/sip/elp/elp-particulate-matter-history.

Texas Hospital Inpatient Discharge Research Data File (TDSHS). (2015). Texas Department of State Health Services, Center for Health Statistics, Austin, Texas (2010-2014).

The Centers for Medicare and Medicaid Services (CMS) (1990). ICD-9-CM coding and reporting official guidelines. American Hospital Association, American Medical Record Association, Health Care Financing Administration, National Center for Health Statistics. Journal of the American Medical Record Association, 61(10), 1–107.

Tong, D.Q., Wang, J., Gill, T.E., Lei, H., and Wang, B. (2017). Intensified dust storm activity and Valley fever infection in the southwestern United States. Geophysical Research Letters, 44(9), 4304–4312. https://doi.org/10.1002/2017GL073524

Touloumi, G., Atkinson, R., Le Tertre, A., Samoli, E., Schwartz, J., and Schindler, C., (2004). Analysis of health outcome time series data in epidemiological studies. Environmetrics, 15, 101–117.

Tylee, A., and Walters, P. (2007). Under-recognition of anxiety and mood disorders in primary care: why does the problem exist and what can be done? Journal of Clinical Psychiatry, 68, 27–30.

Van Pelt, R. S., Shekhter, E.G., Barnes, M.A., Duke, S.E., Gill, T.E., and Pannell, K.H. (2020). Spatial and temporal patterns of heavy metal deposition resulting from a smelter in El Paso, Texas. Journal of Geochemical Exploration, 210, 106414.

Vineis, P., Foraster, F., Hoek, G., and Lippsett, M. (2004). Outdoor air pollution and lung cancer: recent epidemiological evidence. The International Journal of Cancer, 111, 647-652.

Weaver, E.A., and Kolivras, K.N. (2018). Investigating the Relationship Between Climate and Valley Fever (Coccidioidomycosis). EcoHealth, 15(4),840–852. https://doi.org/10.1007/s10393-018-1375-9

Weil, T., De Filippo, C., Albanese, D., Donati, C., Pindo, M., Pavarini, L., Carotenuto F., Pasqui, M., Poto, L., Gabrieli, J., Barbante, C., Sattler, B., Cavalieri, D., and Miglietta, F. (2017). Legal immigrants: invasion of alien microbial communities during winter occurring desert dust storms. Microbiome 5(1), 32.

Weissman, M. M., Wickramaratne, P., Nomura, Y., Warner, V., Verdeli, H., Pilowsky, D. J., Grillon, C., and Bruder, G. (2005). Families at high and low risk for depression: a 3-generation study. Archives of general psychiatry, 62(1), 29–36. https://doi.org/10.1001/archpsyc.62.1.29

Winquist, A., Klein, M., Tolbert, P., Flanders, W. D., Hess, J., and Sarnat, S. E. (2012). Comparison of emergency department and hospital admissions data for air pollution time-series studies. Environmental Health. 11, 70. https://doi.org/10.1186/1476-069X-11-70

World Health Organization (WHO). (2016). Depression and other common mental disorders: global health estimates. https://apps.who.int/iris/handle/10665/254610.

World Health Organization (WHO). (2021, May 19). Ambient Air Pollution: A Global Assessment of Exposure and Burden of Disease -2016 report. https://apps.who.int/iris/handle/10665/250141

Xu, X., Wang, G., Chen, N., Lu, T., Nie, S., Xu, G., Zhang, P., Luo, Y., Wang, Y., Wang, X., Schwartz, J., Geng, J., and Hou, F. F. (2016). Long-Term Exposure to Air Pollution and Increased Risk of Membranous Nephropathy in China. Journal of the American Society of Nephrology: JASN, 27(12), 3739–3746. https://doi.org/10.1681/ASN.2016010093

Yang, Y.R., Chen, Y.M., Chen, S.Y., and Chan, C.C. (2017). Associations between long-term particulate matter exposure and adult renal function in the Taipei metropolis. Environmental Health Perspectives. 125, 602–607.

Zhang, X., Zhao, L., Tong, D., Wu, G., Dan, M., and Teng, B. (2016). A Systematic Review of Global Desert Dust and Associated Human Health Effects. Atmosphere, 7(12), 158. https://doi.org/10.3390/atmos7120158

Zhang, Y., Ma, Y., Feng, F., Cheng, B., Wang, H., Shen, J., and Jiao, H. (2021). Association between PM10 and specific circulatory system diseases in China. Scientific Reports, 11(1), 12129. https://doi.org/10.1038/s41598-021-91637-x

Zhao, N., Qiu, J., Zhang, Y., He, X., Zhou, M., Li, M., Xu, X., Cui, H., Lv, L., Lin, X., Zhang, C., Zhang, H., Xu, R., Zhu, D., Lin, R., Yao, T., Su, J., Dang, Y., Han, X., Zhang, H., Bai, H., Chen, Y., Tang, Z., Wang, W., Wang, Y., Liu, X., Ma, B., Liu, S., Qiu, W., Huang, H., Liang, J., Chen, Q., Jiang, M., Ma, S., Jin, L., Holford, T., Leaderer, B., Bell, M.L., Liu, Q., and Zhang, Y. (2015). Ambient air pollutant PM10 and risk of preterm birth in Lanzhou, China. Environment International, 76, 71–77. https://doi.org/10.1016/j.envint.2014.12.009

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/m^3 increments in maximum PM_{10} 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 $\mu g/m^3$ 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).

References

Tong, D.Q., Wang, J.X.L., Gill, T.E., Lei, H., and Wang, B.Y. (2017). Intensified dust storm activity and valley fever infection in the southwestern United States. Geophysical Research Letters. 44(9):4304–4312.

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.

Contact Information: ecmolina@miners.utep.edu
ficus_em@hotmail.com