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Assessment of Major air Pollutants, Impact on air Quality and Health Impacts on Residents: Case Study of Cardiovascular Diseases

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Abstract
There is increased focus on renewable energy, environmental protection and sustainable development in the sectors of transportation, hence this has necessitated a lot of studies into the types of transportation mechanism and their impact on our environment. Aside other major pollutants, fossil fuels have catered to the energy demands of an increasingly busy and industrialized society and cities, but has also seen objections as to their adverse consequences on the environment and how much pollution it contributes to the environment. Due to the forced restrictions and lockdowns from Covid-19, which saw an extremely minimal usage of conventional transportation across cities, it was observed that pollution levels in cities across the India for example, drastically slowed down just within few days (Mahato *et al*, 2020), same has been the report in many other cities across the world. This underlines the impact which industry, human activity and traffic has on the environment, by the quality of air and how much of an effect it has on the people who live in such regions.

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Introduction

The need for mobility and the proliferation of industrial waste, manufactured goods, local production, and transport channels we have evolved over many years, from the years of the locomotive trains, steam carriages and even animal dragged carriages, coal mines et.c have had some of the greatest impacts on environment and humans and is ever increasing (Balzotti *et al*, 2020). This demonstrates how the need to move from point to point, or make refined goods and production of services is most paramount for humans, to not just move around, but to also be able to move cargo and goods from place. The demand for these kinds of goods and services have doubtless been in the highest demand in recent history, especially in ever increasing numbers of people moving from rural to urban centers for the prospects of work, business or just some other opportunities (Min *et al*, 2020). Sadly, increase in population and movement of people in these places undoubtedly increases the population density of said areas, hence a surge in human waste disposal, carbon emissions in transport, and increased industrial waste. In case of traffic, it wouldn't probably be a major problem as some other interventions and alternative routes can sometimes be preferred to ease the malignant traffic gridlocks and the massive amounts of people moving within cities for their activities.

To emphasize the impact of urbanization on a rise in health problems in various regions, Matsha *et al*, 2012 suggests that urbanisation, demographic and epidemiological changes have made diabetes one of the chief causes of non-communicable diseases in South Africa.

With this increase in the demand for transportation, manufacturing, domestic production of goods and services, also came the demand for fuels that power majority of vehicles, hence the rise of a big issue growing out of the effort to tackle the transportation problem.

Askariyeh *et al*, 2020 suggests that the unfortunate consequence of this boom in population and urban activity is the attendant increase in the amount of carbon emissions from cars, trucks, diesel engines, and even motorbikes. Of course, industrial pollution, forest fires, dump fires, toxic chemicals, domestic air pollution and many other factors contribute to a very large extent to the pollutants that alter air quality significantly. Thus, in efforts to mitigate climate change and the impacts of carbon emissions on the environment, there is great need to ascertain the exact impact of these factors and work towards implementing more environmentally friendly practices in transport and industry.

Background

This research aims to x-ray the most common pollutants found in locations, and also to work around the most prevalent ones found across different locations, which greatly contribute to pollution in the environment, and measuring it against the reported cases of cardiovascular, respiratory or some other related form of illness, which rise from the pollutants affecting air quality, in extension the wellbeing of residents and individuals living in these areas.

Generally, the amount of emissions measured in cities and communities are cumulative, including domestic pollution, industrial, and other sources of the pollution, which are being tackled separately on their own metrics, but we attempt to isolate the emissions and pollution that arises primarily from traffic and pollution arising from transportation (Schultz *et al*, 2017).

With the rise of alternative energy and electric vehicles, this will go a great length into shedding light into how much we can improve on the emissions into our environment and may also help to bring about more attention to be paid into alternative forms of energy that are equally effective, but with less adverse implications on the environment and by extension the health and well-being of people in these areas. Results from the studies of (Pederson *et al*, 2017) suggest that there is a rising quest for clean energy and fuel alternatives, I hope to bring to bear what might be the benefits of reducing mass or increasing use of carbon-based fuels in vehicles and industry, or even in the incineration of waste and gaseous waste disposal, encouraging the reduction in usage more environment friendly practices in industry and transportation, and for people to opt for alternatives.

Statement of Problem

Mahato *et al*, 2020 suggests that majority of times, we may find that the sources of air pollution are quite diverse, and that they do not usually contain the same types of chemicals. This suggests that for every given location, there are a wide range of varying factors that may be responsible for such chemicals, for example, in an industrial area, we may find chemicals that are consistent with the kind of emissions that are being given out as residue of processing of chemicals and some other materials. However, there is a possibility of having a common pollutant in the air which is spread across very wide ranges of space, which may have a more uniform source, and this is one of what we hope to find out. In many regions, there are reported cases of similar diseases, and illnesses, which can be traced back to the environmental pollutants, and usually the cause of this are not usually well investigated and mitigated, this has become a problem for many communities, hence, if there is any sharp spike in the presence of certain identified particles and toxic substances in the air, it will need to be investigated for its cause and efforts be made to shut eliminate the subsequent risk or eliminate the risk completely (Pederson *et al*, 2017).

Aim & Objectives

This research work aims to isolate the most common chemical particles and pollutants found to contribute to the toxicity of air; and we hope to achieve the following objectives at the end of our research work

1. To measure the amount of pollutants found in the air around urban centers, residential and industrial areas within weekdays and weekends.
2. For each location, to isolate the most common pollutants found in the air
3. To determine by inference, the source and how much of a relationship these spikes in pollutants around the study areas are found to be involved in cases of cardiovascular diseases reported in such areas.

Research Questions

This research work aims to answer the following questions

1. What are the most common pollutants found in the air in any location?
2. Has there been any increase in concentrations in the air, and what likely causes?
3. For any given location, is there a reflection on the environment and ailments of people living there which are consistent the types of chemicals found in the air pollutants?

Literature Review

According to Schultz *et al*, 2017, The problem of air pollution is a global one. Cities and towns all over the world suffer this, and this has also adversely affected the health of many. International guidelines have been exceeded for emissions of toxic air, with about 300 million children worldwide breathing it. This air pollution, both indoor and outdoor are linked to 1 in 10 deaths in children under 5 years of age, and out of these, about 20% can be attributed to outdoor air pollution. Urban centres contribute some of the most as a result of burning of fuels. Based on the proximity of people to the sources of these pollutants in the air, especially from traffic, it is paramount to keep an eye and make a track of mitigation protocols.

Formerly tested by a road site in the city of Florence (Italy), the developed IMP has been operated therein across a 1-year measuring campaign (01/02/2016 to 31/01/2017) to provide 1-h concentrations of CO, NO2 and CO2, and 1-h values of traffic flows and vehicle speed. In this study, the results from the monitoring movement, along with observations of main meteorological parameters from a locus station in the city centre, have been evaluated. To provide deeper insight into the role played by emissions from road traffic, the examination has been sorted by period of the year and day of the week (weekdays vs. weekends). Also, a correspondence analysis has been executed among all measured parameters. Following the wind roses over the whole metropolitan area, the polar plots of pollutant concentrations have been constructed. A linear regression model and an ANN have been applied to investigate the influence of local road traffic and meteorological parameters on NO_2 and CO_2 concentrations. Observed CO concentrations are very low (at maximum 0.58 mg/m3), and thus were withdrawn from the study. As expected, both NO_2 and CO_2 concentrations are higher during the cold months, i.e. when heating is an additional emission source to road traffic.

Following the predominant SE wind sector (occurring 25.4–26.9%), the highest NO_2 concentrations result from SE contributions, encompassing both local (road traffic) and far away (background) emission sources. In the cold months, tributary peaks of NO_2 concentrations are linked to local and far away. In the warm months, the weight of local road traffic is higher during the working days than in the weekends. In cold months, concentrations of CO_2 are associated to both native road traffic and background emissions from SE during the working days, while they are only linked to local road traffic in the weekends. In the warm months, contributions to CO_2 peak concentrations, mostly coming from SE, are likely due to local road traffic, being higher during the working days than in the weekends. Application of the multi-regressive framework to the NO_2 concentrations showed that the ANN improves the score vs. the linear model, with the overall r2 ranging 0.49–0.73 vs. 0.37–0.57. Scores related to the CO_2 concentrations were lower, with r2 ranging 0.17–0.47 (linear model), and 0.33–0.67 (ANN). Meteorological parameters explain most of the total r2 of NO_2 concentrations, particularly during the cold months (89–97%), with the contribution of road traffic parameters not exceeding 19%. Basically, the same scenario applies to CO_2 concentrations, with meteorological parameters explaining 73–96% of the total r2, and road traffic constraints not exceeding 27%. In the near future, additional air pollutant sensors (e.g. O_3, VOCs, PM2.5, PM10) will be shared into the IMP so as to allow a more thorough air pollution study, possibly involving extra meteorological parameters (e.g. rainfall, solar radiation, atmospheric stability) and data/estimates of emission sources other than road traffic. A possible work's improvement might involve the implemented statistical models, which, after properly trained as in the current work, could be tested in their air pollution concentration forecasting capability (G. Gualtieri *et al*. 2017).

Emissions from fossil fuels are of course a major contributor, as we see from a study showing that being highly in need of oil products, mainly gasoline and diesel, the French transport sector has been shown to be the main emitter of Particulate Matter (PMs) with critical levels inducing harmful health consequences for urban dwellers (*C. Magazzino et al, 2020*).

From the research carried out by A. Banica *et al*, in Romania, 2017, they found that despite the industrial deterioration, air pollution lingers as a major issue in Romanian cities. As in many other urban regions, in Iasi city the traffic is one of the main causes of air pollution which has a great environmental impact, also exposing population's health to a high risk. The study focused on the small scale inspecting the spatial and temporal unpredictability of air pollution in a very important and frequently circulated crossroad, Podu de Piatra. By making use of various data from air pollution observing posts and resident meteorological data, both, measurements and field observations, the study weighs the relationship between traffic intensity, the existence of pollutants and the showing of susceptible population in an area that is one of the hot zones of air pollution in Iasi. The goal is to apply a spatial exposure assessment model which pools together proximity-based and dispersion models in order to estimate the overall impact of transport on air pollution. The GIS permits to incorporate spatial data, manage it, examine it, and proffer answers to spatial questions. Thus, the outcomes of this study are that:

Air circulation adds to the increase of pollutant concentration, relatively, on different sides of the paths;

1. Monitoring stations have difficulties in giving precise estimations with the wind speed variation;
2. The lowest estimation of NOx has been obtained along the street in 19th April at 6 AM when the wind is perpendicular to the street axis, while the highest was record on 20th April at 18 PM when the wind is parallel to the street axis; to help assessing the representativeness of data from national air quality system.

With many countries looking into efforts to mitigate the adverse effects of air and environmental pollution, (X. Lu *et al*) Suggests that over the past thirty years, China has been making incessant exertions to sever the problem of pollution from economic growth, with the eventual goal of attaining a society based on sustainable development and ecological civilization.

Air Pollution Monitoring

Air pollution has been shown to be a major universal risk factor for ill-health and Death, and in their study, they employed Google Street View (SV) mapping automobiles with an Aclima environmental intelligence fast-response pollution measurement and data integration platform (Aclima, Inc., San Francisco, CA). By means of these vehicles, they repeatedly measured daytime concentrations of black carbon particles (BC), NO, and NO2 on weekdays, over an entire year for every road within varied residential, commercial and industrial areas of three different locations in the USA, NO, and NO2 were found to be crucial pollutants whose sources include vehicular traffic, shipping, industrial combustion, cooking, and heating (Apte *et al*, 2020).

Though most major monitoring systems are not so affordable, low cost and easy-to-use air pollution monitoring systems are available, which provide inhabitants and communities with chances to monitor the local air quality that can directly influence their daily lives. Personal exposure to air pollution is a key connection between ambient air pollution and health effects on humans. However, assessing individual exposures and ascribing exposure to sources poses substantial challenges because of the spatial and temporal inconsistency of pollutants and trouble in guesstimating the time people spend in different types of places, while commuting in traffic, cooking in the house, etc.

Current U.S. regulatory NAAQS requirements require use of a narrow range of monitoring technologies [Federal Reference or Federal Equivalent Methods (FRM or FEM)], which are usually costly to employ in a condensed monitoring network, especially when including infrastructure like electrical power, platform, security, and also with the expert needs, in that air pollution sensors can be used for compliance monitoring of sources, both at the sources, and at the facilities as well as helping industries monitor emissions, reduce produce damage, and improve worker safety (Synder *et al*, 2020).

Pollutants

Studies by Dekker *et al*, 2019, show that according to the tests in their model that are based on MAC City and GFAS emissions, more than half of the CO near ground levels in November of 2017 were as a result of residential and commercial combustion, with some other contributors being industrial combustion and of course, traffic. They found that the overall background CO. With NO2, also a contributing factor to the general pollution index in contributing factors for disease, Achakulwisut, *et al*, 2019, worked on finding if existing proof is inadequate to conclude as to whether a low-concentration brink exists for NO2, beneath which there is no hazard of asthma development in Children, and whether the relationship is direct or indirect. Assuming a log-linear association between NO2 concentration and outcomes, they applied a counterfactual concentration of 2 ppb, the 5th percentile of the lowest possible exposure concentrations reported in separate studies by Khreis and colleagues. This method adopts that long-term exposure to NO2 less than 2 ppb implies no extra hazard of pediatric asthma cases.

There is an indication that the industrial and residential sectors have huge possibilities in getting emission levels of air pollutants and COS down, while also implementing policy to replace energy sources, to achieve significant cuts in CO2 and other main air pollutants simultaneously. We can agree with the deduction in the prior research on the CDM projects in China, that show how the replacement of coal for natural gas in the industrial sector has significant reductions in emission as a co-benefit (Lu, *et al*, 2019).

Air Pollution and the COVID-19 Pandemic

Scientific evidences gathered in various literature accentuate the significant influence of severe exposure to air pollution on the spread of COVID-19 and its mortal impacts, though the possible consequence of an airborne virus exposure has not still been clearly demonstrated (*C. Copat et al., 2020*).

The nationwide lockdowns in many countries have proven to have drastically reduced the pollutants in the air, hence the lockdowns due to the COVID-19 (SARS-CoV-2) pandemic has led to improvements in air quality across the Globe. A study estimates the changes in the six criteria air pollutants (PM2.5 and PM10, NO2, O3, CO, and SO2) during the lockdown across India (Singh *et al*, 2020).

In the current health crisis caused by the pandemic, it is observed that air pollution has wielded a considerate impact on the transmission of and infection by COVID-19 (Z. Zhang *et al*., 2020) and that polluted air is the most significant environmental risk factor for all-cause mortality. It has amplified the risk of cancer, chronic pulmonary and cardiovascular diseases, and caused the loss of at least 100 million disability-adjusted life-years (Karan *et al*, 2020), all these which have been observed to be some of the highest contributors to mortality from the COVID-19 infection.

Air pollutants have been found to upsurge host vulnerability to respirational viral contagions by growing epithelial penetrability to viral receptors and plummeting surfactant production, for example, In Italy, a study showed an upsurge in the environmental concentration of NO2 connected with an upsurge in acute respiratory diseases by 4%. Exposure to Sulphur dioxide (SO2) has also been related to a rise in influenza infections.

This idea is also supported by (Contini and Costabil, 2020), that protracted exposure to air pollution has been connected to acute respiratory swelling, asthma attack, and mortality from cardiorespiratory ailments in numerous studies. Particles with aerodynamic diameters less than 2.5 _m, PM2.5, are regarded as some of the foremost environmental health risk influences, causing several million deaths per year globally.

Wu *et al*, 2020, in a nationwide cross-sectional study found that an increase of only 1 μg/m3 in PM2.5 is linked with an 8% increase in the COVID-19 death rate (95% confidence interval [CI]: 2%, 15%). The results were statistically substantial and strong to secondary and sensitivity analysis.

Also, in a study involving three French cities by*C. Magazzino et al., 2020*, the outcomes presented evidence of a direct affiliation between air pollution and COVID-19 mortality in France, confirming preceding study concerning environmental factors involved in viral infection spread.

Climate Change and Air Pollution

Climate can affect air quality, and vice versa; both can directly or indirectly affect the health of humans. The two main consequences of climate change on air quality are the degrading the removal processes (dispersion, precipitation) and amplifying the chemical components in the atmosphere. These will affect primary pollutants like soot particles, and secondary pollutants like ozone and sulphate particles.

There is some indication that in some areas (e.g. in northern Europe and Poland), climate change could fairly better air quality, chiefly due to alteration in long-range atmospheric air pollution transportation. As climate change influences on air quality differ globally, more local valuations are required, particularly in low and middle-income nations that presently have more concentrations of pollution in the air. Taking reliable methods across studies would enable better comparisons of these regional assessments. (H. Orru *et al*, 2017)

Health Risks Asssociated With Air Pollution

Air pollution and certain air pollutants have been found to be responsible for an array of illness and a source of health hazards which have been observed across many communities and regions around the world.

Air pollution has been deemed of the great killers of our age. in 2015, air pollution was responsible for 6·4 million deaths worldwide: 2·8 million from household air pollution and 4·2 million from ambient air pollution in the same year, tobacco caused 7 million deaths, AIDS 1·2 million, tuberculosis 1·1 million, and malaria 0·7 million. In the absence of decisive and effective control, ambient air pollution is expected by 2060 to cause between 6 million and 9 million deaths per year (P. J. *Landrigan, 2016*).

C.A. Pope, *et al*. 2020, believe that much has changed in the last 25 + years regarding evidence of long-term air pollution exposure contributing to risk of deaths. Results from (Quian Di *et al*, 2017) research in on Association of Short-term Exposure to Air Pollution

With Mortality in Older Adults, show that air pollution is related with an upsurge in daily mortality rates, even at levels well below the present standards.

According to Carré *et al*., 2017, For many years, a causal association has been alleged amid air pollution and some human health conditions. Particulate matter (PM) and ground-level ozone (O3) are Europe's most challenging pollutants in terms of harm to human health, followed by benzo (a) pyrene (BaP) and nitrogen dioxide (NO2) with main sources from transport and energy, and thus concludes that both animal and human epidemiological research supports the idea that air pollutants cause defects during gametogenesis leading to a drop in reproductive capacities in exposed populations. Air quality has an influence on overall health as well as on the reproductive function, thus augmented awareness of environmental protection matters is wanted among the general public and the ruling classes.

Considering Cardiovascular diseases, (Balakrishnan *et al*), finds that numerous research from across the world, including some from India, have provided evidence for the association of air pollution with cardiovascular and lung diseases, though a large amount of this suggestion is from settings more developed than India, evidence from studies of the health impact of short-term exposure to air pollution indicate comparable responses in the Indian population with those in other nations. Also, (Brook, 2008) believes that It remains uncertain whether there is a cumulative increase in health risk linked with long-term exposure that is totally independent from the combination of critical effects that arise over days to weeks, but severe exposure to airborne pollutants increases the risk of cardiovascular illnesses as well.

Kyung-Duk *et al*. 2017 also makes claims that allergic diseases in children are a key public health concern, and prior research has proposed that exposure to traffic-related air pollution (TRAP) is a major risk factor. The research has naturally measured TRAP exposure using traffic metrics, such as distance to main roads, or by modeling air pollutant concentrations; conversely unpredictable connotations with pediatric allergic illnesses have usually been found. Employing road nearness and concentration, it was beforehand found out that there was a relationship between TRAP and atopic eczema among about 15,000 children who live in Seoul, Korea, greatly inhabited and vastly contaminated city in which traffic is a key emission cause. The study targeted to carry out a comparative analysis by making use of modeled air pollution concentrations and thereby observe the dependability of the relationship. They studied the associations of individual-level annual-average concentrations of NO2, PM10, and PM2.5 while tallying them against symptoms and diagnoses of three pediatric allergic diseases including asthma, allergic rhinitis, and atopic eczema.

Evidence of the relationship between traffic-related air pollution and frequency of atopic eczema in children, centered on a characteristic population in a greatly urbanized city in which traffic is a key pollution source. Reliable outcomes showed that using both traffic metrics and air pollution concentrations established the link. As people in megacities have a tendency to to live near large roads, full of activity for easy access to transportation, the amount of the affected children and the degree of risk would be huge. Their recommendations were that, based on protracted data including early air pollution contact and exposure to common triggers of allergies should additionally investigate the relationship with the occurrence and increase of allergic diseases, and deliver policy references to reduce the hostile health impacts of traffic-related air pollution mainly for children living in big cities.

Another study from Schultz *et al*., 2017, posits that Lung function in early life has been shown to be a significant forecaster for top lung function in adults and later decline. Reduced lung function per se is related with higher morbidity and mortality. With this review, the study aimed to summarize the current epidemiological evidence on the effect of traffic-related air pollution on lung function in children and adolescents. They focused in particular on time windows of exposure, small airway involvement, and vulnerable sub-groups in the population. Findings from studies published to date support the idea that contact over the entire childhood age range appears to be of significance for lung function development. They couldn't find any sure data to back indication of sup-group effects bearing in mind gender, sensitization status, and asthma status, even though a possibly solider consequence may be present for children with asthma. The long-term effects into adulthood of contact with air pollution during childhood remains mysterious, but existing findings suggest that these shortfalls may be spread into later life. In addition, more research on the consequence of exposure on small airway function is necessary.

The precise systems by which air pollution affects the lungs and airways are not known. It has been hypothesized that oxidative stress and airway inflammation are important processes. It has for instance been suggested that inhaled particles provoke the generation of reactive oxygen species. This, as well as direct damage by highly oxidative gases such as ozone and NO2, induces oxidative stress and inflammatory responses. Epigenetics has been suggested as one of the links among exposure to air pollution and respiratory health effects, for instance through methylation of genes taking part in immune-mediated inflammatory response. In studies of human histological lung tissue, associations have been observed between exposure to high PM levels and small airway remodeling by greater amounts of fibrous tissue and smooth muscle cells. Studies investigating exhaled nitric oxide in humans support the belief that inflammatory processes may play a role for the observed respiratory health effects by exposure to air pollution. Nitric oxide is an established biomarker of airway inflammation, and several studies show a relation between exposure to air pollution and increased levels of the exhaled fraction of nitric oxide (FeNO). This has been observed for short-term exposures, long-term exposures, indicators of traffic-related air pollution, and even in children with no past accounts of airway damage.

Hilker *et al*, 2019 state that "Traffic-related air pollutants (TRAPs) are of concern, because on-road traffic is often a major source of air pollution in urban environments (Belis *et al*., 2013; Molina and Molina, 2004; Pant and Harrison, 2013) where population densities are greatest—in Canada, it is estimated that one third of the population live within 250 m of a major roadway (Evans *et al*., 2011)—and it is within these near-road regions TRAP concentrations are generally highest (Baldwin *et al*., 2015; Jeong *et al*., 2015; Kimbrough *et al*., 2018; Saha *et al*., 2018)".

As a result of forced restrictions, the level of pollution across major cities around the country radically reduced within few days, which attract debates as to the effectiveness of lockdowns as unconventional measures to be applied for monitoring air pollution (Ghosh *et al*, 2020).

Previous Works

Research work carried out by Balzotti *et al*, 2020, aimed at exploring a simulation tool ranging from vehicular traffic and environmental impact, suggests that the influence of vehicular traffic on society is enormous and multi-layered, comprising economic, social, health and environmental facets. The issues are compound and difficult to model since it necessitates to contemplate traffic patterns, air pollutant emissions, the chemical reactions and dynamics of pollutants in the atmosphere.

Based on their findings, they propose further research and findings be made on the following aspects

1. Extend the tool to road networks to better capture environmental effects.

2. Analyze other chemical reactions.
3. Exploit the dependence on time of emissions to compare pollution levels between weekends and working days.

For us to comprehend the basic sources and causes for rising concentrations, further analysis of raw measured data on specific routes and regions is essential. In general, traffic induced air pollutant concentrations are affected by both regional and local emissions, and being able to differentiate between the influences of these sources allows their comparative influence to be more properly assessed (Hilker *et al*, 2019).

This would necessitate our research to narrow down on the types of emissions on these routes, attendant health risk factors and their causative pollutants found along such environments to determine which need more attention and mitigation of their effects for residents of such locations, with the times in which they seem more prevalent, and why.

Analytical Methods from Previous Studies

Recent studies from India by Amann *et al*, 2017, made use of the AQI, "which is usually based on pollutants criteria where the deliberation of an individual pollutant is transformed into a sole index using appropriate aggregation method, and the sub-indices for entity pollutants at a monitoring station has been calculated based on 24-hour mean (8 h for CO and O3) data and health breakpoint range (CPCB, 2015)".

Min *et al*, 2020 also worked on finding the "Association between exposure to traffic related air pollution and pediatric allergic diseases based on modeled air pollution concentrations and traffic measures in Seoul, Korea: a comparative analysis", they assessed the impact of Traffic related air pollution (TRAP).

To measure the impact of TRAP among children, they projected annual average concentrations of NO2, PM10, and PM2.5 at the investigated children's home addresses in 2010 using universal kriging and land use regression models alongside regulatory air quality monitoring data and geographic physiognomies. Then, they also assessed odds ratios (ORs) of the three allergic diseases for interquartile surges in air pollution concentrations after correcting for individual risk factors in mixed effects logistic regression.

Methodology

Introduction

We will work to show our way of systematically providing answers to our research questions. Essentially, will lay out the procedure by which the we will go about relating, assessing and forecasting the relationships between pollutants measured in the atmosphere and the rate of reported cardiovascular diseases in chosen locations.

Weather and Air Quality data

In this research, we will make a case study of the USA to make assessments of the air quality data provided by weather and monitors around regions of the country, provided by the United States Data catalog resource (catalog.data.gov) to measure the results against the data on cardiovascular disease recorded and collected to enable us to draw a correlation between them.

Isolating the traffic impact on pollution and air quality will take random data sets from different locations, and states, this will make it possible to Isolate the traffic-related emission and help us with an accurate measure.

Data Collation, Analysis, and Presentation

For this research, we will make use of the Python Programming language, and requisite libraries and modules for aggregation, analysis, and presentation of the data and results to relay the kind of results we expect to have.

Data Sources

Our primary air quality data source from pre-generated data files, collected from the United States Environmental Protection Agency. This dataset of the air quality data provides us a very robust information structure that will make it possible to extract and utilize properly for our research goals, and our cardiovascular disease data is obtained from the National Cardiovascular Disease Surveillance Data, National Vital Statistics System (NVSS)

Data Description

Air Quality Index (AQI) data for this research comprises States, Counties, years, Days of air pollutants measured in the air, with amounts, From "Good Days" to "Hazardous Days". This description gives us a glimpse into how much of the years (2014 - 2018) records more variation in AQIs.

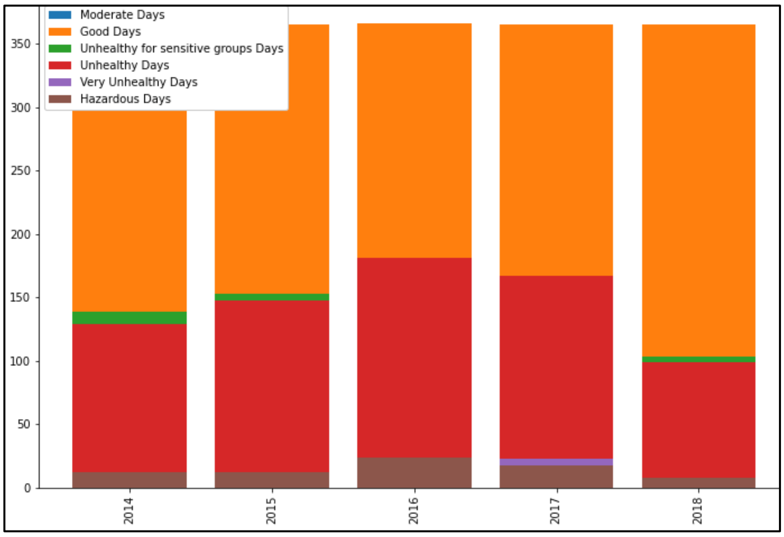


Fig 1: Showing Plot of AQI by year from 2014 to 2018

From fig.3.1 above, we observe that a lot of unhealthy days have been recorded between the years 2014 to 2018, with recorded good days a little somewhat above average 50% to 70% of good days.

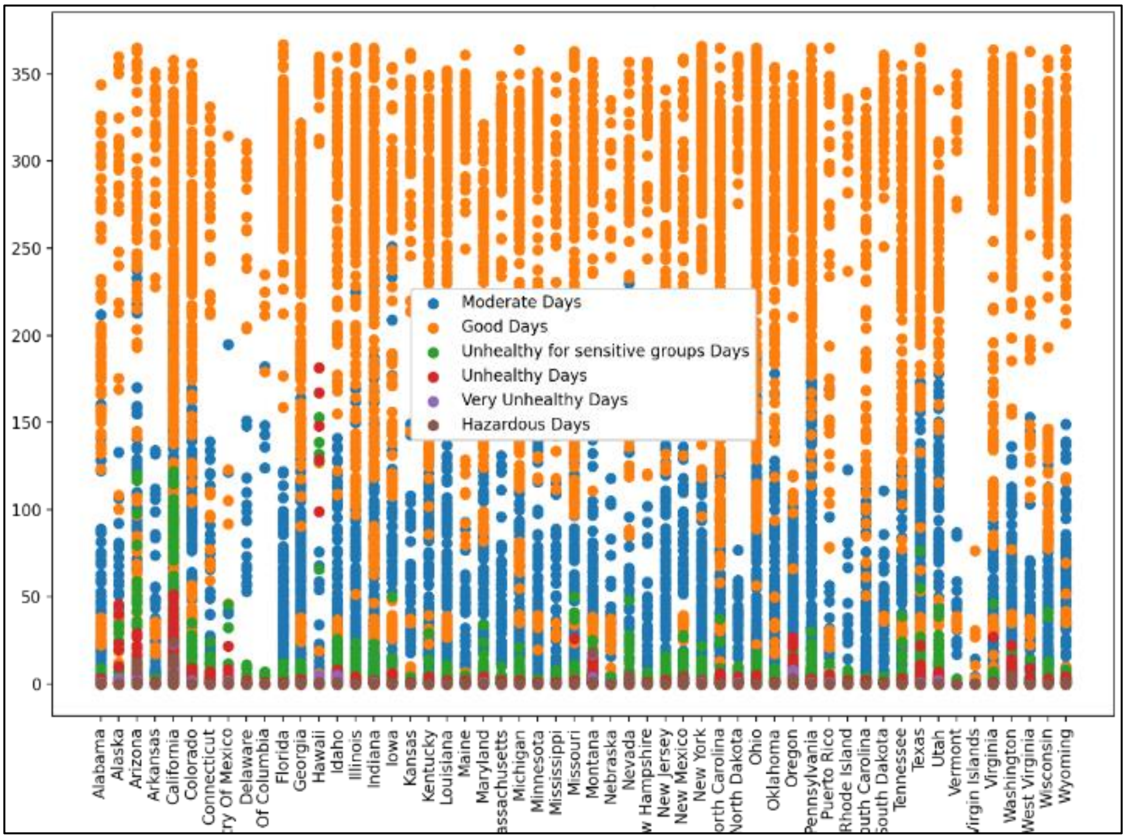


Fig 2: Showing AQI of all states for 5 years (2014 - 2018)

Fig.3.2 shows a scatter plot of the days of observed AQI in all states in the USA, showing California having the highest level of unhealthy and hazardous AQI, relative to the number of days of AQI measured. District of Columbia and the Virgin Islands show the lowest number of Measured AQI days observed in the year, hence the lowest representation in our dataset.

Dependent Variables

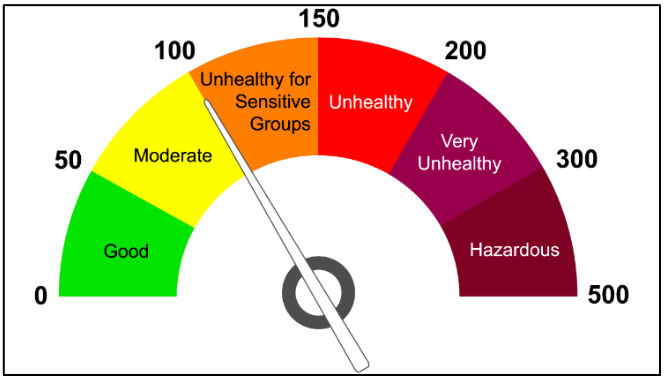
The major dependent variable for our research is the "Data_Value_Alt" value from the cardiovascular disease dataset, which shows numbers of reported cases of cardiovascular diseases (Heart Attack, Stroke, Heart Disease, Coronary Heart Disease, Major Cardiovascular Disease & Heart Failure) per 1000 as shown in fig. We intend to look out for the

Independent Variables

The independent variables in the case of our research are the days, and the relative impact they have on the rate of cardiovascular diseases reported in the selected areas of study.

Aside the data of the individual pollutants measured, the concentration of these pollutants are aggregated in an AQI spectrum, which has a range from 0 to 500, which indicates which levels are observed from Healthy, to Hazardous. For our study, we ignore Good (Healthy) AQIs and Moderate AQIs because we assume, they will have very negligible to no adverse impact on health, which is what we're trying to measure. Instead, we select the following:

i)Unhealthy Days for sensitive groups ii) Unhealthy Days iii) Very Unhealthy Days
iv) Hazardous Days



Source: Oklahoma Department of Environmental Quality

Fig 3: Chart showing the AQI spectrum indicating the levels of concentration in pollutants measured in air.

Days of Carbon Monoxide (CO): Number of days of CO measured, out of 365 days

Days of Nitrogen I Oxide (NO2): Number of days of NO2 measured, out of 365 days

Days of Ozone: Number of days of Ozone measured, out of 365 days

Days of Sulphur IV Oxide (SO2): Number of days of SO2 measured, out of 365 days

Days of Particulate Matter -2.5: These are particles of smoke, chippings, droplets or some other particulate matter which have diameters with is 2.5microns or less.

Days of Particulate Matter -10: This comprises particulate matter measured in the atmosphere that are 10 microns or less, but not equal or less than 2.5 microns.

Dependent Variables

Dependent variables for this study are Six cardiovascular diseases reported by counties in the selected states of the USA.

1. Acute Mycocardial Infarction (Heart Attack)
2. Stroke
3. Diseases of the Heart (Heart Disease)
4. Coronary Heart Disease
5. Heart Failure
6. Major Cardiovascular Disease

Control Variables

For this research, we will take three breakout variables from our cardiovascular disease data (Race, Gender & Age), hence we will lookout for a relationship between cardiovascular disease and these breakout numbers.

Statistical framework

Working with our data set, we aim to employ multiple linear regression, it will chart a map for us as to the most consistent pollutants responsible for the bad air quality in selected regions based on the regression coefficients, showing how much influence they have on each dependent variable, and also to pinpoint the place of the outliers, why the high volumes, then we can determine if their prevalence is significant enough to suggest a high contribution to the observed cardiovascular diseases in that area

$$Y_i = f(X_i, \beta) + e_i$$

Y_i = dependent variable

f = function

X_i = independent variable

β = unknown parameters

e_i = error terms

Research Tools

Our research will be implemented by use of Python PL for our data aggregation and analysis. Python provides for us a very robust environment and highly adaptable modules for our work; some of which we may not need for this research work, would typically include some, but not necessarily all of these namely:

1. **NumPy:** NumPy (Numerical Python) is the fundamental package for numerical computation in Python; it contains a powerful N-dimensional array object. It has around 18,000 comments on GitHub and an active community of 700 contributors. It's a general-purpose array-processing package that provides high-performance multidimensional objects called arrays and tools for working with them. NumPy also addresses the slowness problem partly by providing these multidimensional arrays as well as providing functions and operators that operate efficiently on these arrays.
2. **Pandas:** Pandas (Python data analysis) is a must in the data science life cycle. It is the most popular and widely used Python library for data science, along with NumPy in matplotlib. With around 17,00 comments on GitHub and an active community of 1,200 contributors, it is heavily used for data analysis and cleaning. Pandas provide fast, flexible data structures, such as data frame CDs, which are designed to work with structured data very quickly and intuitively
3. **Matplotlib:** Matplotlib has powerful yet beautiful visualizations. It's a plotting library for Python with around 26,000 comments on GitHub and a very vibrant community of about 700 contributors. Because of the graphs and plots that it produces, it's extensively used for data visualization. It also provides an object-oriented API, which can be used to embed those plots into applications
4. **Scikit-Learn**
5. **Statsmodels.api**

Research Questions

This research work aims to answer the following questions

1. What are the most common pollutants found in the air in any location?
2. Has there been any increase in concentrations in the air, and what likely are the causes?
3. For any given location, is there a reflection on the environment and ailments of people living there which are consistent with the types of chemicals found in the air pollutants?

Expected Results

We expect to see an average consistency in the air quality measured from these regions, and some outliers, which will give us more insight into the demographics, probable cause, and effect of spikes in hazardous air quality observed in some locations, on the community and related cardiovascular disease conditions, especially cardiovascular diseases reported in such areas. This will help to set a course for future research, and also inform decisions in environmental protection policy and fossil fuel usage in automobiles.

The ongoing concern for many nations and communities is the ever-increasing air pollutant concentrations, which have significantly increased the chance and predisposition to adverse health conditions, thus we seek to find workable pathways around mitigation of such adverse consequences of our daily and production-induced pollution problems.

Results

We have extracted results from our datasets, the distribution of our control variables.

Below is a breakdown representation of the AQI relative to the control variables (Race, Age & Gender) – Breakouts, showing the influence of these demographics on the cardiovascular diseases under study.

Table 1: Showing the distribution of cardiovascular diseases by gender

Cardiovascular Disease	Male (per 1000)	Female (per1000)
Acute Mycocardial Infarction (Heart Attack)	164.7	111.0
Stroke	75.1	87.7
Coronary Heart Disease	269.4	201.7
Heart Failure	66.1	74.0
Diseases of the Heart (Heart Disease)	402.6	330.6
Major Cardiovascular Disease	504.2	432.2

Table 2: Showing the distribution of cardiovascular diseases by race

Cardiovascular Disease	Non-Hispanic White (per 1000)	Hispanic (per 1000)	Non-Hispanic Black (per 1000)	Other (per 1000)
Acute Mycocardial Infarction (Heart Attack)	150	43.2	134.5	126.3
Stroke	95.1	54.1	85.4	84.2
Coronary Heart Disease	253.4	131.2	244.3	233.8
Heart Failure	82.9	37.5	59.0	29.3
Diseases of the Heart (Heart Disease)	425.7	245.6	428.1	297.5
Major Cardiovascular Disease	530.0	320.3	536.0	383.0

Table 3: Showing the distribution of cardiovascular diseases by Age

Cardiovascular Disease	18-24 (per 1000)	25-44 (per 1000)	45-64 (per 1000)	35+ years (per 1000)	65+ years (per 1000)	75+ years (/1000)
Acute Mycocardial Infarction (Heart Attack)	2.0	9.5	117.2	193.2	436.4	673.6
Stroke	2.0	8.5	51.0	113.0	312.0	613.5
Coronary Heart Disease	2.0	4.2	35.4	98.4	304.5	637.4
Heart Failure	1.0	5.0	54.5	106.3	294.6	541.93
Diseases of the Heart (Heart Disease)	1.0	12.0	62.5	131.5	338.2	599.5
Major Cardiovascular Disease	1.3	18.8	90.7	180.0	438.6	789.3

For our analysis, we select randomly 5 States in the USA

- California
- Arizona
- Wyoming
- Florida
- Alabama

Multiple Regression Analysis Results, based on OLS Regression Models

Table 4: Showing multiple regression coefficients for Acute Mycocardial Infarction (Heart attack)

AQI Variable	State Regression Coefficients				
	California	Arizona	Wyoming	Florida	Alabama
Unhealthy for sensitive group Days	0.0327	-0.0425	-0.0783	-0.1065	0.6546
Unhealthy Days	-0.1101	0.3266	0.4570	0.5596	-0.4585
Very Unhealthy Days	-0.1058	-0.8574	0.6763	3.395e-13	-2.7335
Hazardous Days	0.1102	0.0734	1.1100	1.225e-12	9.845e-15
Days of CO	0.1215	5.725e-14	-0.1286	-0.6274	8.64e-15
Days of NO2	0.0367	0.1001	0.0379	0.0390	0.0107
Days of Ozone	-0.0026	-0.0147	-0.0016	0.0042	-0.0012
Days of SO2	0.8232	-0.0238	0.0117	0.0161	-0.0745
Days of PM2.5	-0.0076	-0.0157	0.0105	0.0027	-0.0165
Days of PM10	-0.0057	-0.0134	-0.0013	0.0019	0.0129

Table 5: Showing multiple regression coefficients for Stroke

AQI Variable	State Regression Coefficients				
	California	Arizona	Wyoming	Florida	Alabama
Unhealthy for sensitive group Days	0.0024	-0.0145	-0.1211	0.0070	-0.1666
Unhealthy Days	-0.0149	0.0754	-0.3390	-0.7416	0.2584
Very Unhealthy Days	0.0968	-0.5207	-2.8643	1.82e-12	-0.2384
Hazardous Days	0.0610	0.0917	-3.2408	7.441e-13	-5.872e-15
Days of CO	0.0883	-6.776e-14	0.1209	0.5066	1.041e-14
Days of NO2	-0.0037	0.0463	-0.0225	-0.0199	0.0270
Days of Ozone	0.0008	-0.0020	0.0016	-0.0019	4.251e-05
Days of SO2	-0.8640	-0.0021	-0.0328	-0.0086	0.0132
Days of PM2.5	0.0008	-0.0009	-0.0094	-0.0006	0.0040
Days of PM10	-0.0016	-0.0021	0.0019	-0.0001	-0.0021

Table 6: Showing multiple regression coefficients for coronary heart disease

AQI Variable	State Regression Coefficients				
	California	**Arizona**	**Wyoming**	**Florida**	**Alabama**
Unhealthy for sensitive group Days	0.0680	-0.0420	-0.2624	-0.3390	0.4807
Unhealthy Days	-0.2167	0.7651	0.5790	1.5902	-0.3981
Very Unhealthy Days	-0.3865	-2.5254	-0.6447	1.363e-12	-2.7270
Hazardous Days	0.1135	-0.1668	-0.0931	4.932e-12	1.975e-14
Days of CO	0.0347	2.351e-13	0.9608	-1.7355	2.786e-14
Days of NO2	0.0858	0.1669	0.0402	0.1070	0.0085
Days of Ozone	-0.0073	-0.0189	-0.0017	0.0127	-0.0021
Days of SO2	3.5775	-0.0660	-0.0053	0.0466	-0.0595
Days of PM2.5	-0.0181	-0.0238	0.0161	0.0086	-0.0105
Days of PM10	-0.0090	-0.0154	-0.0009	0.0064	0.0144

Table 7: Showing multiple regression coefficients for Heart Failure

AQI Variable	State Regression Coefficients				
	California	**Arizona**	**Wyoming**	**Florida**	**Alabama**
Unhealthy for sensitive group Days	-0.0213	0.0438	-0.1445	-0.0274	0.0991
Unhealthy Days	0.0582	-0.1207	0.1670	0.1168	0.3156
Very Unhealthy Days	0.2513	-0.5477	-2.8631	1.925e-13	-3.5155
Hazardous Days	0.0236	-0.0996	-2.7794	6.989e-13	1.435e-14
Days of CO	0.5033	1.322e-14	-1.0970	0.1733	1.479e-14
Days of NO2	-0.0332	-0.0428	0.0415	-0.0053	0.0793
Days of Ozone	0.0035	0.0158	-0.0007	-0.0004	-0.0030
Days of SO2	-2.4547	0.0064	-0.0207	-0.0024	-0.0319
Days of PM2.5	0.0069	0.0170	-0.0025	-0.0002	0.0004
Days of PM10	0.0014	0.0148	4.745e-06	7.62e-06	0.0159

Table 8: Showing multiple regression coefficients for major cardiovascular disease

AQI Variable	State Regression Coefficients				
	California	**Arizona**	**Wyoming**	**Florida**	**Alabama**
Unhealthy for sensitive group Days	0.0377	0.0544	-2.0788	-0.2437	-0.3531
Unhealthy Days	-0.1649	0.2817	0.9309	-1.3543	-0.0325
Very Unhealthy Days	0.4357	-3.2877	-18.1380	2.948e-12	-3.4324
Hazardous Days	0.3484	-0.2100	-17.5141	1.076e-11	5.67e-14
Days of CO	1.6833	4.708e-13	7.3075	-0.1088	9.692e-14
Days of NO2	0.0122	0.0563	0.0343	0.0279	0.0424
Days of Ozone	0.0017	0.0199	0.0016	0.0065	-0.0030
Days of SO2	-4.0177	-0.0294	-0.2105	0.0168	0.0112
Days of PM2.5	-0.0029	0.0207	0.0342	0.0073	0.0121
Days of PM10	-0.0113	0.0196	0.0070	0.0063	0.0031

Table 9: Showing multiple regression coefficients for heart disease

AQI Variable	State Regression Coefficients				
	California	**Arizona**	**Wyoming**	**Florida**	**Alabama**
Unhealthy for sensitive group Days	0.0436	0.0479	-2.6263	-0.3401	-0.1991
Unhealthy Days	-0.1590	0.2128	2.9164	0.6142	-0.5566
Very Unhealthy Days	0.0330	-2.2960	-16.8566	2.149e-12	-2.8941
Hazardous Days	0.2035	-0.2318	-15.1889	7.813e-12	4.361e-14
Days of CO	0.8237	3.464e-13	-7.2619	-1.8624	7.336e-14
Days of NO2	0.0402	0.0227	0.2601	0.1048	-0.0096
Days of Ozone	-0.0021	0.0152	-0.0022	0.0152	-0.0023
Days of SO2	-0.4253	-0.0250	-0.1362	0.0515	0.0023
Days of PM2.5	-0.0086	0.0147	0.0352	0.0117	0.0073
Days of PM10	-0.0088	0.0152	0.0020	0.0088	-0.0009

The results from our analysis show that from all states in the US, the age brackets of 75+ years old account for the highest rates of all cardiovascular diseases, followed closely by 65+, then by 35+ and then 25 years and below. This indicated that, as expected, age plays a very major role in susceptibility to cardiovascular diseases more than anything else, as we do not see such sharp disparity when we consider the other variables, i.e., Gender and Race.

Considering Race, we have non-Hispanic White leading the charts in Heart Disease, Coronary Heart Disease, Heart Attack, Heart failure, and only lagging "Non-Hispanic Black" in Major Cardiovascular Diseases, which is trailing behind "Nin-Hispanic" in all categories, with the Hispanic following after, then other race.

Gender on the other hand swings heavily on the side of the male gender, with Coronary Heart, Heart Attack, Heart Diseases, and Major Cardiovascular diseases reported among males, and Females only reporting more cases of Heart failure and Stroke per 1000.

CO in Wyoming shows a very huge impact on Major cardiovascular disease, with a coefficient of 7.3075; coronary heart disease, with a coefficient of 0.96, the most significant contribution to the Very Unhealthy days Variable. Unhealthy and very unhealthy days, constituted by fractions of influence by the air Majorly CO, NO2, and Ozone, make up the strongest factors with positive regression coefficients against the value of cardiovascular disease reported rates.

Heart disease in Florida shows a very strong relationship by very strong regression coefficients of 0.6142, with the contributing gasses to be majorly (NO2) between the number of unhealthy days with a coefficient of 0.1048. Florida also sees the little impacts of SO2, Ozone, CO, NO2, PM2.5, and PM10 which range between coefficients of 0.03 and 0.0019, with NO2 as the highest contributor to Heart attacks with 0.03. Strokes in Florida appear to be significantly influenced by the prevalence of CO with a coefficient of 0.5. Coronary heart disease shows a considerable positive link with NO2 (0.107), and little Ozone, SO2, PM2.5, and PM10, at 0.0127, 0.0466, 0.0086, and 0.0064 respectively.

Heart disease in Wyoming also showing a regression coefficient of 2.92 on unhealthy days, with NO2, also being a major contributor by 0.26, while heart attacks are contributed to by SO2, and NO2

In California, SO2 accounts for the highest cause of Heart attacks, with a coefficient of 0.8232, followed by CO with a coefficient of 0.1215, and then NO2 with 0.0367. Strokes in California are also seen to be affected by CO being the highest contributor to Strokes by a coefficient of 0.08. Coronary heart diseases appear to have a very strong contributor in S)2, with a coefficient of 3.5773, followed by NO2 with 0.0858, and CO with 0.0347. Heart failure shows, a coefficient of 0.5033 of CO, being the chief contributor; Major Cardiovascular diseases, show a strong causal coefficient in CO (1.6833), followed by NO2 and Ozone, with 0.0122, and 0.0017 respectively.

Arizona shows Stroke contribution by NO2, with a coefficient of 0.0463, coronary heart disease, with the main contributor being NO2 with a coefficient of 0.1669; Heart failure shown to be lightly contributed to by Ozone, PM2.5, and PM10, with 0.0158, 0.017, and 0.0148 respectively. Major cardiovascular disease is caused by a small amount of NO2 (0.0563), Ozone, PM2.5, and PM10 (0.0196), being the lowest.

Alabama shows positive regression coefficients on just a few of the pollutants under study, probably owing to the relatively low prevalence of the pollutants, showing NO2, highest in contributing to the rate of Strokes, with a coefficient of 0.027, followed by SO2 with 0.0132 and then PM2.5 at 0.004. Heart Failure is shown to be influenced by NO2, in Alabama with a coefficient of 0.739

Discussion

Values for the number of days recorded in the data used in this study were standardized, especially for the number of days of exposure that have been measured. To have a good fit, varying numbers of the days had to be adjusted up or down to a scale of 365 days, by a standardization formula of

“aqi_2014_2018["$test_days"] = (aqi_2014_2018["Days_with_AQI"] / 365) * aqi_2014_2018["$test_days"]”

With “$test_days” being the days under observation for each of the independent variables.

The relationships we have attempted to highlight among the different chemical properties and the values of cardiovascular diseases being reported, do not appear to have direct relationships when combined in a multivariate space, based on the results from our data analysis, but a more subtle relationship which is more reflected from the individual contributions to the movement of the values we obtain from the isolation of individual items on the dataset.

Results show three major causal pollutants from all 5 states, which dominate averagely all the positive results in different diseases, with SO2 being the highest contributor to 3 out of the 5 cardiovascular diseases in this study, namely Heart Attack, Coronary Heart Disease, and Stroke, followed by CO, and NO2. In states like California, the prevalence of CO is from majorly traffic, and open combustion. NO2 also results from human activities in fossil fuel combustion (coal, gas, and oil) especially fuel used in cars. SO2, on the other hand, is linked with the activities in the:

- Oil and gas industry
- Pipeline operations
- Marine operations
- Metal smelting
- Pulp and paper production

Sulfur dioxide is responsible for breathing problems, particularly lung function, and can cause irritation of the eyes. Sulfur dioxide also causes irritation in the respiratory tract and upsurges the risk of tract infections, from coughs, mucus secretion, while also aggravating conditions such as chronic bronchitis and asthma, as immediate effects.

In the long-term, we also observe from the regression models, that more of the influencing factors to the rate of cardiovascular diseases are linked with the streak of unhealthy AQI days, as reflected in the table we see how much of an influence the chief pollutants found on this study to be predisposing factors in Stroke, Heart attacks, Major cardiovascular diseases, and coronary heart disease.

Conclusion

Generally, we can conclude that the biggest and most significant factor in the increased rate of most cardiovascular diseases, is partly a long term effect of transportation, and vehicular traffic, then secondarily, from industrial activities, as we observe that the most common denominator when considering the air pollutants in this study are all from major sources fossil fuel combustion, which in extension we can extrapolate and infer that denser cities and locations with high traffic volumes are liable to have a higher prevalence of these pollutants in the atmosphere, which will, in turn, result in more cardiovascular diseases reported, as we can see with California.

The industrial dependence on carbon fuels also accentuates the risks posed on the environment and residents of localities, as this contributes significantly to the presence of these pollutants that have been found in the air. Thus, aside finding alternative energy sources for the auto industry and in transport, more attention must also be drawn to the application of alternative sources of energy in industry and less dependence on carbon-based energy sources for the running of industrial operations in manufacturing and industrial waste disposal.

Limitations

The study has a few limitations, one of which borders on unequal number of AQI days for separate pollutants across the years, which we had to regularize by the formula highlighted above. Also, from some of the key variables in our AQI Datasets, namely: Unhealthy Days, Unhealthy for Sensitive Groups Days, Very Unhealthy days, Hazardous days; do not specify which among the pollutants contribute the most to this metric, as they can also be made up of particulate matter, aside the other toxic pollutants observed, this made it a little tricky to decide exact effects of these variables on the related cardiovascular diseases, hence reducing the reliability of these variables in indicating relationship, or predicting effect of any of the pollutants on the health reliably.

A few uncertainty sources may also affect the regression results in this study. The main reason comes from limitations in this research, which was, finding the most effective way to isolate certain key values from the datasets without obscuring the significance of other values on the dataset, as it combines very many independent but relevant data and uncorrelated values within the same dataset. Hence, we recommend further research with different datasets for each key statistic, to show a better fit for general correlation and regression on these many independent variables contributing to cardiovascular diseases to show particular individual effects.

Future Directions

To seek out more clarity and results in regard to this study, further work can be carried out to determine the reasons responsible for the Male gender accounting for the majority of cases in almost all reported cases of cardiovascular disease, as it would help in mitigation and planning to help more men in this bracket, those of ages from 35 and above, and also with women in handling risk and predisposing factors of Heart Failure and Stroke. Also, measurement and tracking of traffic and population density might be very helpful in determining the exact level of influence that traffic, industrial and domestic practices and conditions contribute to the pollution problems observed in cities towns. This will be very helpful in charting a most efficient course to curb the hazards that these sources of pollution pose to the communities in which they are found, by mitigating practices and systems.

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