Health effects of ambient levels of respirable particulate matter (PM) on healthy, young-adult population

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HIGHLIGHTS

- Data on respiratory illnesses were obtained for three military bases in USA.
- Particulate matter (PM) concentrations for corresponding periods were also obtained.
- Ambient PM and health outcomes relationship among healthy young-adults was examined.
- Health data were correlated with daily/weekly PM, air quality and weather data.
- Significant adverse health effects corresponding ambient PM levels were observed.

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ABSTRACT

There is an absence of studies that define the relationship between ambient particulate matter (PM) levels and adverse health outcomes among the young and healthy adult sub-group. In this research, the relationship between exposures to ambient levels of PM in the 10 micron (PM10) and 2.5 micron (PM2.5) size fractions and health outcomes in members of the healthy, young-adult subgroup who are 18–39 years of age was examined. Active duty military personnel populations at three strategically selected military bases in the United States were used as a surrogate to the control group. Health outcome data, which consists of the number of diagnoses for each of nine International Classification of Diseases, 9th Revision (ICD-9) categories related to respiratory illness, were derived from outpatient visits at each of the three military bases. Data on ambient concentrations of particulate matter, specifically PM10 and PM2.5, were obtained for these sites. The health outcome data were correlated and regressed with the PM10 and PM2.5 data, and other air quality and weather-related data on a daily and weekly basis for the period 1998 to 2004. Results indicate that at Fort Bliss, which is a US Environmental Protection Agency designated non-attainment area for PM10, a statistically significant association exists between the weekly-averaged number of adverse health effects in the young and healthy adult population and the corresponding weekly-average ambient PM10 concentration. A least squares regression analysis was performed on the Fort Bliss data sets indicated that the health outcome data is related to several environmental parameters in addition to PM10. Overall, the analysis estimates a .6% increase in the weekly rate of emergency room visits for upper respiratory infections for every 10 μg/m³ increase in the weekly-averaged PM10 concentration above the mean. The findings support the development of policy and guidance opportunities that can be developed to mitigate exposures to particulate matter.

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1. Introduction

Studies in the medical literature have identified an association between elevated levels of particulate matter (PM) in the “Respirable” size fraction and adverse health outcomes in the general population. These studies have concluded that health effects can
occur even at very low levels of exposure. The peer-reviewed medical literature contains a number of studies that report on the adverse health effects (acute and chronic) associated with exposure to elevated levels of PM.

Studies of human populations exposed to high concentrations of particles major indicated effects of concern for human health. These effects include breathing and respiratory abnormalities, aggravation of existing respiratory and cardiovascular disease, alterations in the body’s defense systems against foreign materials, damage to lung tissue, carcinogenesis and premature death. The major subgroups of the population that appear to be most sensitive to the effects of PM include individuals with chronic obstructive pulmonary or cardiovascular disease or influenza, asthmatics, the elderly and children (USEPA, 2004).

While these effects have been observed in the general population, which includes the very young, the aged, and other susceptible groups, there are only a limited number of studies in the literature that report on the association between PM levels and health effects observed in the healthy, young-adult subgroup. Even these limited existing studies in this area are more qualitative in nature and tend to lack the rigor provided by more statistically significant analyses. This gap may be attributable to the lack of robust data sets containing information on PM related illnesses and corresponding data on exposure to PM.

The principal objective of this research is to determine the strength of the relationship between observed levels of PM and outpatient diagnoses of respiratory disease in the healthy, young-adult subgroup. The scope of this research, which is epidemiological in nature, also includes the examination of the interrelationships among other air pollution parameters and weather-related factors and the health outcome data.

2. Health effects of PM: literature review

The acute and chronic health effects of airborne particles have been vigorously investigated for five decades since the London episode (USEPA, 1999; Davis et al., 2002; and Pope and Dockery, 1999). PM has been linked to numerous adverse health effects including increased hospital admissions and emergency room visits, respiratory symptoms, exacerbation of chronic respiratory and cardiovascular diseases, decreased lung function, and premature mortality (USEPA, 1999). Stanek et al. (2011) reviewed several published studies on short-term exposure to different PM compositions and relationship between the factors or sources and health effects. Collectively, these studies suggest that cardiovascular effects may be associated with PM2.5 from crustal or combustion sources, including traffic, but at this time, no consistent relationships have emerged.

Recent concern has been raised about the effect of particulate pollutants on human health following a number of epidemiological studies in cities with different pollutant levels (Dockery and Pope, 1994; Schwartz, 1994a,b; Lippmann et al., 2000; Zhou et al., 2013). These studies show clear correlations between particulate pollutant concentration levels and adverse health effects, especially of the cardiac and respiratory systems in the general population. For example, Zhou et al. (2013) have showed that the PM10 mortality coefficients for overall population and the PM10 exposure coefficients were significantly correlated.

Specific attention is being paid to the particle size fraction capable of being inhaled and reaching the gas exchange region of the lungs. Particles of about 10 µm or less in aerodynamic equivalent diameter (PM10) are capable of reaching the alveoli (the gas exchange region of the lungs) (Rabovsky, 1997), and those measuring between 0.5 and 1.0 µm aerodynamic diameter have the highest possibility of being deposited and retained in the alveoli (Parkes, 1983). Particles also may carry other harmful substances with them to these regions, with the smaller particles having the greatest surface area available for such transport (USEPA, 2003). de Hartog et al. (2009) observed that indoor and personal PM2.5 were not associated with HRV.

The majority of studies in the medical literature involve identifying and evaluating health outcomes in the general population in an urban environment over a lifetime of exposure. A number of studies have reported an association between daily emergency room visits or emergency hospital admissions, lung function test results, various respiratory symptoms and daily PM levels (Pope et al., 1991; Wordley et al., 1997; Chestnut et al., 1991; Vigotti et al., 1996; Xu et al., 1991; and Dab et al., 1996).

Numerous studies suggest that health effects can occur at particulate levels that are at or below the levels permitted under national and international air quality standards. According to the World Health Organization (WHO) and other organizations, no evidence exists that indicates that there is a threshold below which particle pollution does not induce some adverse health effects, especially for the more susceptible populations (e.g., the very young, the elderly, the infirmed, and susceptible populations) (USEPA, 2002a,b). A major issue in the analysis of epidemiological evidence is the role of other criteria pollutants (e.g., O3, CO, SO2 and NO2), effect modifiers (e.g., co-pollutants, individual susceptibility, smoking or age) in associations between health effects and PM (EPA, 2000a). Confounding effects are more likely to occur in areas where industrial activities (e.g., chemical manufacturing and petroleum refining operations) are the source of uncontrolled atmospheric releases of pollutants (Rothman and Greenland, 1998). Toxicological studies suggest that several elements, including aluminum, silicon, vanadium, and nickel, are most closely associated with health impacts, although many other elements, as well as carbon-containing components, have been implicated as well (Rohr and Wyzga, 2012). Furthermore, Rohr and Wyzga also concluded that there are no PM components for which there is unequivocal evidence of zero health impact.

Dockery and Pope (1994) found that respiratory hospital admissions and emergency room visits in the general population increased by approximately 0.8% and 1.0% per 10 µg/m3 of PM in the less than 10-µm size fraction (PM10), respectively. The increase in emergency room visits and hospital admissions for asthmatics was higher at a 3.4% and 1.9% increase per 10 µg/m3 PM10, respectively. Lung function tests showed a decrease of about .15% for forced expiratory volume and a .08% decrease for peak flow per 10 µg/m3 increase in PM10. Pascal et al. (2014) presented an analysis of the short-term associations between particulate matters (PM10, PM10-2.5 and PM2.5) and mortality by causes, age-groups and seasons in nine French cities using a generalized additive Poisson regression model for the 2000–2006 period. A significant effect of PM10 (+.8% CI 95% [2.1, 1.5] for a 10 mg/m3 increase) and PM2.5 (+.7% [1.6]) on all-ages non-accidental mortality whole year was observed. The largest impacts were observed on all-ages cardiovascular mortality during summer for PM2.5 +5.1% [1.8, 8.4]) and PM10-2.5 (+7.2% [2.8, 11.7]).

Evidence from a limited number of toxicological studies suggests that exposure to particles can also increase risk of hospitalization for pneumonia and respiratory infection, aggravating asthmatic symptoms or increase airway reactivity (USEPA, 2003). A number of epidemiologic studies have reported increased risk of exacerbation of asthma with ambient PM exposure. Halonen et al. (2008) measured the levels of particulate air pollution, NO2, and CO in 1998–2004 at central outdoor monitoring sites in Helsinki, Finland. The study evaluated associations between daily pollution levels and hospital emergency room visits for asthma (ICD10: 102–111).
J45–J46) in children aged less than 15 years, and for asthma and COPD (ICD10: J41–J44) in adults (15–64 years) and the elderly (≥65 years). The study findings suggest that the mechanisms of the respiratory effects of air pollution, and responsible pollutants differ by age group.

Smith et al. (2002) compared the post-Gulf War morbidity of US military personnel (a surrogate for a healthy, young-adult subgroup) exposed to PM in smoke from the 1991 Kuwaiti oil well fires with that of unexposed personnel. An ecological study suggested a relationship between PM10 levels and upper respiratory disease in soldiers deployed to Bosnia but failed to show a statistically significant association (Hastings and Jardine, 2002).

In general, chronic respiratory illness and pulmonary function decrement studies are less numerous than acute studies and the findings are inconclusive and, in some cases, inconsistent. Some studies show effects for some health endpoints, but other studies fail to find the same effects. For example, chronic pulmonary studies by several groups of researchers showed no effect for children from airborne particle pollution (Ware et al., 1986; and Neas et al., 1994). In contrast, another group of researchers studying children in US and Canada found significant associations between pulmonary function and PM levels (Raizenne et al., 1996).

Historical evidence has included studies of lung cancer trends, studies of occupational groups, comparisons of urban and rural populations, and case-control and cohort studies using diverse exposure metrics (Cohen and Pope, 1995; Cohen, 2000). Other studies suggest that living in a city with higher PM levels may be associated with an elevated risk of lung cancer amounting to an increase of about 10–15% above the lung cancer risk in a cleaner city (Pope et al., 2002; Abbey et al., 1999; and Beeson et al., 1998).

As in the case of mortality studies, U.S. multi-city studies (Schwartz, 1996; not reanalyzed) likely provide the most precise estimates for relationships between ambient PM10 levels and increased risk for hospitalization. In these studies increases of 5% in hospital admissions for cardiovascular disease and 8% and 6% in hospital admissions for COPD or pneumonia (respectively) per 50 μg/m3 increase in PM10 were reported. As noted in the single-city studies, effect estimates for cardiovascular admissions generally range from about 1% to 10% per 25 μg/m3 PM2.5 or PM10, and effect estimates for respiratory admissions generally range from about 5% to 25% per 25 μg/m3 PM2.5 or PM10.

Pope et al. (2002) compared data on particulate and gaseous air pollution with data on the cause or death among 500,000 people followed for 16 years by the American Cancer Society. After adjusting for risk factors, as well as possible regional differences, the researchers found that every 10 μg/m3 increase in fine particles produces a 6% increase in the risk of death by cardiopulmonary disease, and 8% for lung cancer.

In recent years increased awareness on the adverse effects of poor air quality has led to such episodic control measures as ozone action days. These campaigns mostly target "at-risk" groups such as the elderly and the very young. Healthy, young-adults, on the other hand, are generally believed by the medical community to be less affected by increased PM levels (Shaughnessy, 2005). There is a need to study the relationship between the PM levels in the ambient air and the health impacts on this subgroup as well.

To summarize, studies have linked PM to lung cancer, heart and lung disease, reduced lung function and asthma exacerbation primarily in the sensitive subgroups. These studies have also predicted rate increases in health outcomes as a function of increases in ambient particulate levels. The same associations are not apparent, however, for the healthy, young-adult segment. It is not clear from the current literature whether there is any difference in the association between the health effects in this subgroup and ambient PM and the same health effects in the general population.

3. Study methodology

The purpose of this study is to investigate the strength of association between health outcomes as measured by emergency room/clinic (i.e., outpatient) diagnoses vis-à-vis short-term changes in ambient PM levels, other air quality parameters, and weather features. In this section, details of the data used for analysis and analysis methods are discussed.

3.1. Study population

The study population consists of active duty military personnel, who are used as a surrogate for a healthy, young-adult subgroup. To test the hypothesis this research will involve the correlation of site-specific air quality, weather-related and health outcome data at several locations within the United States. Locations selected for analysis were restricted to US military bases because of the availability of out-patient medical information and because active duty military personnel are a “captive” population with respect to access to medical care. That is, service members stationed at a base are more likely to seek health care from an on-base medical facility, unlike civilian populations that may have a choice for medical care from alternative hospital facilities. This approach limits the number of hospital databases that need to be accessed to obtain the health outcome data and reduces the possibility that some records may not be captured because of patient selection for medical care from alternative hospital facilities.

The health outcome data reflect the number of medical visits in general and do not distinguish between first visits and follow-up visits; consequently, the data capture the number of visits and not the number of illness episodes. The health endpoints used in the research represent active duty personnel who were successful in obtaining doctor’s attention, and who were then diagnosed with a respiratory illness. Predisposing factors such as age (≥40 years), illness (e.g., asthma), physical and emotional stressors, life-style choices (e.g., smoking and alcohol use), or unique genetic traits that may alter susceptibility to PM levels were not included as factors in this analysis.

3.2. Evaluation sites

Evaluation sites among a number of military bases located in US are selected based on the following criteria:

- The candidate “test” evaluation sites would include USEPA designated non-attainment areas for PM10 and/or PM2.5.
- At least one “control” site should be located in an area with a low PM level to determine whether associations between the data sets are maintained under these conditions.
- To insure that statistically significant samples are obtained, only those bases with active duty populations of 10,000 or more were considered.
- The proximity of the base to an ambient air quality monitoring station was an important factor. Only USEPA air-monitoring stations located within 1–2 miles of the base were considered.

Using these criteria the following military bases were selected for study:
1. Fort Bliss, Texas (test site) is located in a USEPA-designated non-attainment area with respect to national ambient air quality standards (NAAQS).
2. Fort Benning, Georgia (test site) is located in an area where PM\(_{2.5}\) levels marginally meet the new NAAQS for PM\(_{2.5}\).
3. Fort Lewis, Washington (control site) is located in an area designated by USEPA to be in attainment with NAAQS for PM\(_{10}\) and PM\(_{2.5}\).

3.3. Health outcome data

Health outcome data were obtained from the Army Medical Surveillance Activity (AMSA). AMSA operates the Defense Medical Surveillance System, an executive information system whose database contains up-to-date and historical daily data on diseases and medical events (e.g., hospitalizations, ambulatory visits, reportable diseases, HIV tests, acute respiratory diseases, and health risk appraisals).

The data are listed in categories according to the International Classification of Diseases, 9th Revision (ICD-9); a system that provides for a common method for disease designation. Total daily counts were obtained for the period 1998 to 2003 for each of the nine category ranges shown in Table 1. These codes were selected because, as the medical literature suggests, there is a known or suspected association between exposure to elevated levels of PM and the diseases represented by these codes.

These data were normalized as a function of the base's active duty population (expressed as the total number of visits for respiratory related symptoms per 1000 service members). The denominator data was based on the yearly average active duty populations for each of the test sites for the years 1998 through 2003 for Fort Bliss, and 1998 through 2002 for Fort Benning and Fort Lewis.

3.4. Ambient air quality and weather-related data

Air quality and weather-related data were obtained from the USEPA's Aerometric Information Reporting System (AIRS) database that has been the agency's repository of criteria air pollutant monitoring data since the 1970s. Ambient data are available from more than 4000 monitoring stations located nationwide. Hourly data, from 1998 through 2004, were obtained from all monitoring stations located within 1–2 miles of the study sites for the following parameters: PM less than 10 microns (PM\(_{10}\)), PM less than 2.5 microns (PM\(_{2.5}\)), ozone (O\(_3\)), sulfur dioxide (SO\(_2\)), nitrogen dioxide (NO\(_2\)), and carbon monoxide (CO). In addition, various weather-related data were obtained; these included: wind speed and direction, temperature, barometric pressure, relative humidity, and solar radiation. Data on these factors are obtained to account for the seasonal factors that may contribute to respiratory-related health outcomes.

3.5. Analysis methods

Time-series analysis of morbidity data has a popular tool in addressing the association between health outcome and environmental factors, and has been applied widely to investigate the health affects associated with exposure to airborne PM and other pollutants. In these studies investigators recognized the importance and the challenge of adjusting for the potential confounding effects of: (a) the levels of other pollutants; (b) weather; and (c) seasonal variations in mortality due to influenza, which might be associated erroneously with the seasonal variations in PM. For example, sulfur dioxide (SO\(_2\)) and nitrogen dioxide (NO\(_2\)) are precursors in the formation of PM and they are also separately regulated pollutants that can independently cause adverse respiratory-related health effects at sufficiently high concentrations (Ackermann-Liebrich and Rapp, 1999, Schlesinger, 1999). Neuberger et al. (2004) conducted time series studies in rural and urban areas of Austria and found that ambient PM\(_{2.5}\) was most consistently associated with parameters of respiratory health. Time series studies applying semiparametric generalized additive models showed significant increases of respiratory hospital admissions (ICD 490–496) at age 65 and older.

Time-series studies were employed to identify the associations between daily particulate levels and health effects including morbidity, heart disease, emergency room visits, and respiratory symptoms (Lebowitz et al., 1987; Mazumdar and Sussman, 1983; Ozhaynak and Spengler, 1985; and Samet et al., 1981). These analyses also account for potential time-varying confounders related to weather and season. They also have attempted to account for day-of-the-week and holiday effects on the health-related data sets (Glasser and Greenburg, 1971; Goldstein and Rausch, 1978; and Schimmel and Murawski, 1976).

In time-series studies of air pollution and mortality, the use of generalized additive model (GAM) has become an increasingly popular method in PM related epidemiological studies (Schwartz, 1994a,b; Dominici et al., 2002; Pascal et al., 2014). The popularity of GAM is attributed to it's flexibility to allow for nonparametric adjustments for non-linear confounding effects of seasonality, trends, and weather variables. Dominici et al. (2002) conducted a comparative assessment of 1) Poisson regression with parametric non-linear adjustments for confounding factors; 2) GAM with default convergence parameters; and 3) GAM with more stringent convergence parameters than the default setting. The results of the comparative analysis indicated that estimates were very similar under the first and third methods but were biased upward under the second method. Even with the stringent convergence criteria suggested by Dominici et al. (2002), increased concavity in the data used to fit a semiparametric spatial GAM leads directly to increased downward bias in the estimated standard error of the fitted linear parameter and, consequently, to inflated type I error in the standard significance test of this effect (Ramsay et al., 2003).

Due to its simplicity, a time-series data analysis approach using Pearson Correlation analyses is applied in this research. In addition, a least squares linear regression analysis is applied to model short-term effects (i.e., the number of diagnoses for a specific health outcome) as a function of the various environmental parameters.

Lag time, or the time delay between exposure and the onset of symptoms that prompt the emergency room/clinic visit, is accounted for as well as confounding factors and personal behavior patterns that may affect the association between health outcomes and the environmental data. Lag times of between one to four days have been noted in the literature (USEPA, 2003), and are applied here. Personal behavior patterns (i.e., a potential source of bias) that may affect results include weekend and holiday travel where affected personnel may forego treatment, and decisions not to visit a health care facility, for seemingly minor eye or throat irritations and instead choose to ignore or self-treat the condition. In addition, the temporal availability of health care services will have an impact on how well the health care data matches up with the corresponding environmental data. For example, the daily rate of respiratory related diagnoses will fluctuate sharply when health care facilities such as clinics are closed during the weekends. Collectively, these factors would result in underreporting of acute respiratory-related diagnoses possibly related to PM concentrations and directly impact the association between observed PM levels and the health outcome data, and therefore need to be accounted for in this research.
3.6. Statistical analysis

The raw data were received in text format and converted to a Microsoft® Excel spreadsheet format. The data were then checked to insure that the time series for each of six air quality, seven weather-related, and nine ICD-9 code parameters at each site are continuous. Gaps in the hourly values were identified, as were days for which no data were available. This is a manual process that helps to insure that from a temporal or chronologic perspective the air quality, weather-related and health outcomes data are properly matched for the statistical analyses that will follow.

For each air quality and weather-related parameter for which hourly data was available, summary descriptive statistics (e.g., mean, standard deviation, minimum and maximum values, confidence intervals, etc.) were computed. Additionally, daily (24-h) average, daily maximum observed, and weekly average values were calculated for each site. Other parametric and non-parametric analyses are conducted as appropriate to compare data sets between sites.

Time series analyses were conducted to determine whether there were seasonal influences that may affect the data sets. Seasonal adjustments to the health outcome data set was performed by calculating the average daily number of diagnoses for the related

### Table 1

<table>
<thead>
<tr>
<th>ICD-9 Category</th>
<th>Diagnoses</th>
</tr>
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<tbody>
<tr>
<td>410-414: Ischemic Heart Disease</td>
<td>Acute myocardial infarction, Other acute and sub acute forms of ischemic heart disease, Old myocardial infarction, Angina pectoris, Other forms of chronic ischemic heart disease</td>
</tr>
<tr>
<td>415-417: Diseases of Pulmonary Circulation</td>
<td>Acute pulmonary heart disease, Chronic pulmonary heart disease, Other diseases of pulmonary circulation, Acute pericarditis, Acute and sub acute endocarditis, Acute myocarditis, Other diseases endocardium, Cardiomyopathy, Conduction disorders, Cardiac dysrhythmias, Heart failure, Ill-defined descriptions and complications of heart disease</td>
</tr>
<tr>
<td>420-429: Other Forms of Heart Disease</td>
<td>Acute nasopharyngitis (common cold), Acute sinusitis, Acute pharyngitis, Acute tonsillitis, Acute laryngitis and tracheitis, Acute upper respiratory infection of multiple or unspecified sites, Acute bronchitis and bronchiolitis</td>
</tr>
<tr>
<td>460-466: Acute Respiratory Infections</td>
<td>Deflected nasal septum, Nasal polyps, Chronic pharyngitis and nasopharyngitis, Chronic sinusitis, Chronic disease of tonsils and adenoids, Peritonsillar abscess, Chronic laryngitis and laryngotracheitis, Allergic rhinitis</td>
</tr>
<tr>
<td>470-478: Other Diseases of the Upper Respiratory Tract</td>
<td>Viral pneumonia, Pneumococcal pneumonia, Other bacterial pneumonia, Influenza</td>
</tr>
<tr>
<td>480-487: Pneumonia and Influenza</td>
<td>Bronchitis, not specified as acute or chronic, Chronic bronchitis, Emphysema, Asthma, Bronchiectasis, Extensive allergic alveolitis, Chronic airway obstruction, not elsewhere classified</td>
</tr>
<tr>
<td>500-508: Pneumoconiosis and Lung Disease</td>
<td>Coal worker's pneumoconiosis, Asbestosis, Pneumoconiosis due to silica or silicates, Pneumoconiosis due to inorganic dust, Pneumonopathy due to inhalation of other dust, Pneumoconiosis, unspecified, Respiratory conditions due to chemical fumes and vapors, Pneumonitis due to solids and liquids, Respiratory conditions due to other and unspecified external agents</td>
</tr>
<tr>
<td>510-519: Other Diseases of the Respiratory System</td>
<td>Empyema, Pleurisy, Pneumothorax, Abscess of lung and mediastinum, Postinflammatory pulmonary fibrosis, Other alveolar and parietoalveolar pneumonopathy, Other diseases of the lung, Other diseases of the respiratory system.</td>
</tr>
</tbody>
</table>
ICD-9 Categories for each month across all similar months during the period of record and then subtracting that value from the observed count. For example, for any given day in December, the December monthly average would be subtracted from the daily-observed count to yield a number above or below the average experience for a day in December. After seasonal variations were accounted for the strength of association between each of the data sets was determined using Pearson correlation analysis.

The SPSS® statistical software package was used to generate Pearson correlation and linear regression analyses on the health outcome and environmental data sets. The correlation analysis was conducted in three steps:

- **Step 1** The 24-h average health outcome data were compared against the corresponding 24-h average environmental data.
- **Step 2** The 24-h health outcome data were adjusted to reflect a rate per 1000 service members, converted to weekly average values, seasonally adjusted and compared against the corresponding weekly averaged environmental data.
- **Step 3** The weekly averaged and seasonally adjusted health outcome rates were lagged 1–4 day and compared against the corresponding weekly averaged environmental data.

A least squares linear regression analysis was then performed on the data sets. The ICD-9 Code with the highest statistically significant association to PM10 and PM2.5 observed in Step 3 of the correlation analysis was selected as the dependent variable and regressed against the air quality and weather independent variables that make up the environmental data set. Statistical concerns for estimating short-term effects from analyses of time-series data include:

- Controlling for observed and unobserved factors, such as season and temperature, that might confound the true association between PM levels and health outcomes;
- Accounting for serial correlation in the residuals that might underestimate statistical uncertainty of the estimated risk;
- Selecting the lag of the exposure variable (i.e., the time between exposure and the onset of symptoms); and
- Accounting for behavioral factors that may influence the data (e.g., vacation schedules, holidays, and weekends that may affect outpatient and emergency room visits).

Overall, the data analysis phase of the research was carried out to address a number of questions, including the following:

- What is the strength of association between PM levels measured from ground-based monitoring stations and the incidence of diagnoses of respiratory and cardio-pulmonary diseases based on out-patient (ambulatory) hospital records on a daily basis?
- What are the relationship between PM levels and other pollutants on the incidence of diagnoses of respiratory and cardio-pulmonary diseases?
- What role do weather features (e.g., wind speed/direction, temperature, relative humidity, barometric pressure, etc.) play in the relationship between air quality and the incidence of diagnoses of respiratory and cardio-pulmonary diseases?
- Based on this research methodology, can DoD facilities be identified that are prone to higher incidence of respiratory and cardio-pulmonary diseases because of air quality or other environmental factors?

For the purpose of categorically interpreting the correlation analysis results, the following r-value ranges are used for defining the strength of association between two variables:

- **Weak**: $0 \leq r \leq .33$
- **Moderate**: $.33 < r \leq .66$
- **Strong**: $.66 < r \leq 1.0$

## 4. Analysis results

A comprehensive review of results of the above mentioned analysis are discussed elsewhere (Shaughnessy, 2005). To facilitate the discussion, only a representative set of results is presented in this section. Table 2 presents the results of the correlation analysis for the Fort Bliss data sets.

As seen in Table 2, all but one ICD-9 categories have statistically insignificant (at $\alpha = 5\%$) association between the average weekly rate (per thousand) of diagnoses. Positive, moderate and statistically significant association ($r = .513; p = .011; n = 37$) exists between the average weekly rate (per thousand) of upper respiratory infection diagnoses (ICD-9 Category 460-466 with a 4-day lag) and the corresponding PM10 weekly average data. The association between upper respiratory diagnoses rates and the corresponding PM10 data is strong enough to influence the total diagnoses for all ICD-9 combined (row title: ICD-9 Total/1000).

A series of scatter plots, line drawings and bar charts are made to visualize trends this association for all three sites. Fig. 1 shows two examples in which ICD-9 (category 460-466) diagnosis rates are plotted against.

As can be seen in the scatter-plot in Fig. 1 (a), diagnosis rates for ICD-9 upper respiratory infections weekly clearly show a positive correlation with concentrations of PM10. As seen in Fig. 1 (b), ICD-9 diagnoses are the highest on Mondays and the lowest on Saturday, which is followed by Sunday with second lowest diagnoses rates. As would be expected, the lower diagnosis rate on weekends relative to weekdays is consistent among all ICD-9 categories and for all three sites. It is highly unlikely that the variation in diagnoses between weekdays and weekends is due to PM levels. This variation may be attributable to possible ‘waiting out through the weekend’ rather than seeking immediate medical help. Similar analyses were performed for Fort Lewis and Fort Benning and the full results are available in the dissertation work performed by Shaughnessy (2005). In this paper, only the results for Fort Bliss are summarized.

In addition to the above correlation analyses, a multiple regression analysis was performed on the Fort Bliss data sets with least squares linear regression model of the form:

$$Y = a + b_1X_1 + b_2X_2 + ... + b_pX_p$$

Where:

- $Y = $ independent variable
- $a = $ constant
- $b = $ coefficient of the independent variables
- $X = $ independent variable

The independent variables used in the analysis consisted of the air quality and weather-related data include:

<table>
<thead>
<tr>
<th>PM10</th>
<th>PM10 (Max)</th>
<th>PM2.5</th>
<th>PM2.5 (Max)</th>
<th>Sulfur dioxide</th>
<th>Sulfur dioxide (Max)</th>
<th>Nitrate</th>
<th>Nitrate (Max)</th>
<th>Ozone</th>
<th>Ozone (Max)</th>
<th>Carbon Monoxide</th>
<th>Carbon Monoxide (Max)</th>
<th>Temperature</th>
<th>Temperature (Max)</th>
<th>Relative humidity</th>
<th>Relative humidity (Max)</th>
<th>Wind speed</th>
<th>Wind speed (Max)</th>
<th>Barometric pressure</th>
<th>Barometric pressure (Max)</th>
<th>Solar radiation</th>
<th>Solar radiation (Max)</th>
</tr>
</thead>
</table>
Table 2
Correlation of ICD-9 parameters/1000 with PM$_{10}$ weekly average lagged 0–4 days (Ft Bliss).

<table>
<thead>
<tr>
<th>ICD-9 Parameter (weekly average)</th>
<th>Lag time</th>
<th>0-Day</th>
<th>1-Day</th>
<th>2-Day</th>
<th>3-Day</th>
<th>4-Day</th>
</tr>
</thead>
<tbody>
<tr>
<td>ICD-9 Codes 410-414/1000</td>
<td>r = −.237; p &lt; .165;</td>
<td>r = −.233; p &lt; .165;</td>
<td>r = −.286; p &lt; .086;</td>
<td>r = −.238; p &lt; .157;</td>
<td>r = −.247; p &lt; .146;</td>
<td>n = 37</td>
</tr>
<tr>
<td>ICD-9 Codes 415-417/1000</td>
<td>r = −.295; p &lt; .076;</td>
<td>r = −.295; p &lt; .076;</td>
<td>r = −.329; p &lt; .047;</td>
<td>r = −.329; p &lt; .047;</td>
<td>r = −.343; p &lt; .041;</td>
<td>n = 37</td>
</tr>
<tr>
<td>ICD-9 Codes 420-429/1000</td>
<td>r = −.319; p &lt; .054;</td>
<td>r = −.319; p &lt; .054;</td>
<td>r = −.249; p &lt; .137;</td>
<td>r = −.301; p &lt; .07;</td>
<td>r = −.184; p &lt; .283;</td>
<td>n = 37</td>
</tr>
<tr>
<td>ICD-9 Codes 460-466/1000</td>
<td>r = .489; p &lt; .01;</td>
<td>r = .453; p &lt; .01;</td>
<td>r = .456; p &lt; .01;</td>
<td>r = .461; p &lt; .01;</td>
<td>r = .513; p &lt; .01;</td>
<td>n = 37</td>
</tr>
<tr>
<td>ICD-9 Codes 470-478/1000</td>
<td>r = .096; p &lt; .571;</td>
<td>r = .057; p &lt; .737;</td>
<td>r = .078; p &lt; .646;</td>
<td>r = .248; p &lt; .138;</td>
<td>r = .323; p &lt; .055;</td>
<td>n = 37</td>
</tr>
<tr>
<td>ICD-9 Codes 480-487/1000</td>
<td>r = .255; p &lt; .128;</td>
<td>r = .315; p &lt; .057;</td>
<td>r = .230; p &lt; .170;</td>
<td>r = .225; p &lt; .180;</td>
<td>r = .358; p &lt; .032;</td>
<td>n = 37</td>
</tr>
<tr>
<td>ICD-9 Codes 490-496/1000</td>
<td>r = .272; p &lt; .103;</td>
<td>r = .195; p &lt; .247;</td>
<td>r = .224; p &lt; .182;</td>
<td>r = .331; p &lt; .045;</td>
<td>r = .293; p &lt; .083;</td>
<td>n = 37</td>
</tr>
<tr>
<td>ICD-9 Codes 500-508/1000</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>n = 37</td>
</tr>
<tr>
<td>ICD-9 Codes 510-519/1000</td>
<td>r = −.338; p &lt; .041;</td>
<td>r = −.338; p &lt; .041;</td>
<td>r = −.238; p &lt; .157;</td>
<td>r = −.304; p &lt; .068;</td>
<td>r = −.247; p &lt; .146;</td>
<td>n = 37</td>
</tr>
<tr>
<td>ICD-9 Total/1000</td>
<td>r = −.373; p &lt; .023;</td>
<td>r = −.326; p &lt; .049;</td>
<td>r = −.334; p &lt; .043;</td>
<td>r = −.434; p &lt; .01;</td>
<td>r = −.458; p &lt; .01;</td>
<td>n = 37</td>
</tr>
<tr>
<td>ICD-9 Total adjusted for seasonal influence/1000</td>
<td>r = −.218; p &lt; .199;</td>
<td>r = −.189; p &lt; .263;</td>
<td>r = −.225; p &lt; .180;</td>
<td>r = −.370; p &lt; .024;</td>
<td>r = −.383; p &lt; .021;</td>
<td>n = 37</td>
</tr>
</tbody>
</table>

Notes: p-values are two-tailed.
N/A – Parameter is a constant (all values for Code 500-508 are zero).
Bold emphasis indicates statistical significance at α = .05.

Fig. 1. Ft Bliss ICD-9 (Category 460–466) w/4-Day Lag vs PM10 Weekly Averages.
As noted previously, a split data set was used in this analysis. The data sets used to develop the regression model spanned the period January 2000 through July 2002. Additional data from August 2002 to January 2004 were used to verify the model results.

The ICD-9 Codes 460-466 Weekly Average/1000 (with 0- to 4-day lag periods) data were selected as the dependent variable for regression analysis because in the correlation analysis these data were observed to have the highest association with particulate matter levels. Five regression analyses were run, one for each lag period (i.e., 0–4 days).

Based on these results the linear regression model for estimating the weekly average number of clinic and/or emergency room visits per 1000 active duty service members at Fort Bliss for respiratory conditions related to upper respiratory infections (ICD-9 Codes 460-466) with a 4-day lag period from time of exposure is expressed as:

\[
\log_{10}Y = 2.021 + .005(\text{PM}_{10}\text{Avg}) - 14.803(\text{O}_{3}\text{Max}) + .116(\text{TempAvg}) - .113(\text{TempMax}) - .069(\text{CO–Max}) - .180(\text{WS–Avg}) + .078(\text{WS–Max})
\]

where:

- \(\log_{10}Y\) = Log of the weekly average rate (/1000) of clinic/ emergency room diagnoses for upper respiratory infections (ICD-9 Codes 460466);
- \(\text{PM}_{10}\text{Avg}\) = Weekly average particulate matter (less than 10 micron) concentration (\(\mu\text{g/m}^3\));
- \(\text{O}_{3}\text{Max}\) = Weekly average of the maximum daily ozone concentrations (ppm);
- \(\text{TempAvg}\) = Weekly average temperature value (°C);
- \(\text{TempMax}\) = Weekly average of the maximum daily temperature values (°C);
- \(\text{CO–Max}\) = Weekly average of the maximum daily carbon monoxide concentrations (ppm);
- \(\text{WS–Avg}\) = Weekly average wind speed value (mph); and
- \(\text{WS–Max}\) = Weekly average of the maximum daily wind speed value (mph).

A comparison of the number of weekly emergency room and clinic diagnoses for acute upper respiratory infections predicted by the model and the actual number is presented in Fig. 2. Data from the August to December 2003 split data set were used to populate the model.

4.1. Summary of results

The following observations summarize the analyses results:

1. The correlation analysis using weekly averages suggests a positive, statistically significant (at the \(p < .01\) level) association between the health outcome data adjusted for both the strength of the active duty population and seasonal influence, and PM\(_{10}\) levels in the ambient environmental for the period of record at all three sites. Results suggest that this association is the greatest for the health outcome data involving diagnoses for upper respiratory infections (ICD-9 Code 460-466);

2. Results indicate that for the Ft Bliss test site, a positive, and moderate statistically significant (at the \(p < .01\) level) association exists between the occurrence of adverse health effects in its active duty population and ambient particulate matter levels. This relationship is significant for all time periods in which the health outcome data (the number of diagnoses of upper respiratory infection) was lagged but was the strongest when a 4-day lag was used (\(r = .513\); \(p < .01\); \(n = 37\)). The data also indicate that this association may be the strongest during the March to May timeframe; the period in which particulate matter levels are routinely at their highest.

3. For the period of record, the degree of association between health outcome and environmental data at all sites is proportionate to the average PM\(_{10}\) and PM\(_{2.5}\) levels observed at the individual study sites. For example, at Ft Bliss, where the average yearly PM\(_{10}\) level exceeded the NAAQS yearly standard and the 24-h standard was exceeded on at least 15 occasions during the period of record, a positive, moderate, statistically significant (at the \(p < .01\) level) association between the health outcome and PM\(_{10}\) data was observed.

4. At Ft Benning and Ft Lewis where the yearly average PM\(_{10}\) levels were about the same (41% and 40%, respectively, of the yearly NAAQS standard) and the 24-h standard was not exceeded, there was no statistically significant (at the \(p < .01\) level) association observed.

5. The yearly average PM\(_{2.5}\) values for Ft Bliss and Ft Benning approximated the yearly NAAQS standard. At these sites there was a weak statistically significant association (at the \(p < .05\) and \(< .01\) levels, respectively). At Ft Lewis, however, where the yearly average PM\(_{2.5}\) level was about 77% of the standard, there was no positive, significant association.

Even though the results indicated statistically significant association between ICD-9 diagnosis rates and PM\(_{10}\) data for the non-attainment (test) sites but not for the attainment (control) sites, it cannot be conclusively determined if the effect is only significant for the non-attainment sites. The main reason for this is that the difference between attainment and non-attainment status was not evaluated for statistical significance or p-values.

These results may not be too surprising when comparing them with results seen in the literature for studies involving the general population. For example, for the period of record the mean PM\(_{10}\) concentration at Ft Bliss was 54.57 \(\mu\text{g/m}^3\) (95% CI: 50.55, 58.65) compared to the NAAQS standard of 50 \(\mu\text{g/m}^3\). During the same period the 24-h standard of 150 \(\mu\text{g/m}^3\) was exceeded on at least 15 occasions during the period. These standards are designed to protect the general population and can be seen as a threshold level above which adverse health effects may begin to occur. Therefore, one may expect to see an increase in respiratory symptoms when these standards are exceeded. This is especially true for the sensitive sub-groups such as the very young and the elderly.

5. Conclusions and discussion

This research represents an ecological study and time series analysis of health outcome and environmental data to determine whether an association exists between the data sets. The research results presented in this paper support the hypothesis that short
term changes in ambient concentrations of particulate matter are associated with short-term changes in acute respiratory-related health outcomes in a healthy, young-adult subgroup. Other important contribution of the research is that it links medical data with environmental data to investigate specific health outcomes, and draws on several years of daily data upon which to base a quantitative assessment of this association.

Overall, the analyses predict a 0.6% increase in the rate of emergency room visits at Ft Bliss for upper respiratory infections for every 10 μg/m³ increase in PM₁₀. There is no statistical common ground to compare this 0.6% rate of increase with the 1.0% increase per 10 μg/m³ increase in the PM₁₀ size fraction reported by Dockery and Pope (1994) for the general population. However, the predicted rate of increase in the Ft Bliss population appears reasonable if one assumes that a healthy, young-adult subgroup would be less susceptible to increases in particulate matter levels than the general population.

6. Limitations of the research

Several limitations in the research are observed that likely influence the association between the health outcome and environmental data:

- A review of the time series data for all three sites indicates that behavioral factors, such as vacation schedules and possibly the willingness to “tough out” a medical problem rather than seeking health care, likely impact the daily data. For example, gaps and reductions in the data are evident during weekends (Fig. 1b) and in the time periods associated with the Christmas Holiday.
- Health outcome data do not distinguish between smokers and non-smokers, and asthmatics who may be more sensitive to changes in pollution levels.
- Other atmospheric pollutants and spatial variation in the distance between monitoring stations and study populations likely had an impact on the association between the health outcome and environmental data sets.
- The effect of co-pollutants and potential confounders (CO, NO₂, SO₂, and O₃) is not taken into account in establishing the linkage between PM and health outcomes in young and healthy adult population.
- Environmental data used in the analysis do not account for non-ambient exposures.

6.1. Areas of potential research

The results of this research are consistent with the findings of previous epidemiological studies that have investigated the association between particulate matter and acute symptoms in the general population. Other areas of potential research are listed below:

- The use of ambient air pollution concentrations as a surrogate for actual exposure assumes that all individuals in an area experience identical exposures and ignores differences in activity patterns, indoor/outdoor concentrations, and sub-spatial variability.
- Further research into the heterogeneity of PM is required because health outcomes at specific locations may be due to a difference in PM characteristics.
- Other research needs include further characterization of the effects on the general population and susceptible subpopulations, emissions sources, deposition and fate of PM in the respiratory tract, combined effects of PM and other co-pollutants, and the biological mechanisms involved in the development of adverse health effects.

6.2. Policy implications of the research

The findings of this research support the development of policy and guidance opportunities that can be developed to mitigate exposures to particulate matter. Recommendations that are specific to the operations at military bases include the following:

- Develop strict air quality monitoring and data collection protocols that can be used in subsequent health risk assessments at other military bases where exposure to particulate matter may result in unacceptable health risks.
- Establish a multi-faceted health risk communication program to notify personnel when concentrations of particulate matter may reach critical levels, such as a pollution alert program similar to ozone and smog alert programs developed in many cities.
- Manage personnel activity schedules to avoid prolonged outdoor exposure or heavy physical work in ambient air environments when particulate matter concentrations reach unacceptable risk levels.
- From an operational effectiveness perspective, evaluate the feasibility of issuing personal protective equipment (PPE) such as dust masks to mitigate exposures at least during major dust events.

References


