RELATIONSHIP BETWEEN CRITERIA AIR POLLUTANTS AND PHYSICAL FITNESS MEASURES FROM CHILDREN IN CALIFORNIA

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CHAPTER I

INTRODUCTION

Moderate regular aerobic exercise is routinely recommended to promote good health and well-being. However, negative health impacts may be experienced when individuals exercise in locations with high ambient air pollution. Few studies have examined the association of ambient air pollution with athletic performance, and fewer have examined the relationship of pollution and fitness among school-aged children. Potential health impacts to children are of special concern, due to certain characteristics which may make children more susceptible to the effects of pollutants, such as criteria air pollutants.

Criteria air pollutants consist of the six most common ambient air pollutants in the United States: ozone (O_3), carbon monoxide (CO), nitrogen dioxide (NO_x), sulfur dioxide (SO_2), lead (Pb), and particulate matter (PM_{10} and $PM_{2.5}$). These air pollutants contribute significantly to the overall levels of ambient air pollution, especially in heavily populated areas, and have been associated with a wide range of adverse health outcomes, including asthma, cardiovascular disease, central nervous system disorders, birth defects, miscarriage, and premature death (USEPA, 2008). For each of the six criteria air pollutants, the United States Environmental Protection Agency (EPA) has established national air quality standards that define allowable concentrations in ambient air. The establishment of such standards means that monitoring systems are in place to assess concentrations of these substances in the air. As such, California maintains an extensive air pollution monitoring network and has made the majority of its data publicly accessible. Many areas within the state of California struggle with complying with these air monitoring standards.

During 2006 and 2007, numerous California counties were classified as non-attainment areas for carbon monoxide, ozone, and particulate matter (PM_{10} and $PM_{2.5}$). According to a report by the American Lung Association (ALA, 2009), several cities in California, including Los Angeles, Bakersfield and Visalla-Porterville, remain some of the most polluted in the U.S., with air quality that is likely damaging the health of millions of people.

Yet, the question remains as to whether the concentrations of criteria air pollutants in ambient air can be directly linked to levels of physical fitness in children. In addition to maintaining an extensive air monitoring network, the state of California has established mandatory statewide physical fitness testing. Each spring, this testing is administered to all students in fifth, seventh, and ninth grades. A total of six fitness areas are assessed: 1) aerobic capacity, 2) abdominal strength and endurance, 3) upper body strength and endurance, 4) body composition, 5) trunk extensor strength, and 6) flexibility. Results from the testing are submitted to the California Department of Education (CDE), which maintains a publicly accessible database of aggregate test results on its Web site. This database provides a means for assessing overall fitness of these students at a school, school district, or county level.

This study focuses on data from aerobic capacity and body composition testing during 2006 and 2007 and aims to assess the relationship between physical fitness rates in California schools and those criteria pollutants that were identified as being in non-attainment during this time period.

1.1 Research Questions

The primary research question driving this study is:

Are measures of Aerobic Capacity and Body Composition in school aged children, as evaluated by the California Physical Fitness Testing Program, associated with ambient levels of criteria air pollutants?

In addressing this research question, the following specific aims were developed:

Specific Aim 1: To examine the association between attainment status for CO, O_3, PM_{10}, and $PM_{2.5}$ and measures of aerobic capacity and body composition in children.

Hypothesis 1: Schools located in counties that are in non-attainment for CO, O_3, PM_{10}, or $PM_{2.5}$ will have lower overall passing rates for aerobic capacity testing.

Hypothesis 2: Schools located in counties that are in non-attainment for CO, O_3, PM_{10}, or $PM_{2.5}$ will have lower overall passing rates for body composition testing.

Specific Aim 2: To examine the association between various demographic factors and measures of aerobic capacity and body composition.

Hypothesis 3: Overall passing rates of aerobic capacity or body composition testing will differ by demographic variables (grade, gender, ethnicity, SES)

Specific Aim 3: To examine the association between attainment status for CO, O_3, PM_{10}, and $PM_{2.5}$ and aerobic capacity or body composition in children after adjusting for demographic factors that influence these endpoints.

Hypothesis 4: Schools located in counties that are in non-attainment for CO, O_3, PM_{10}, or $PM_{2.5}$ will have lower overall passing rates for aerobic capacity testing after adjusting for key demographic variables.

Hypothesis 5: Schools located in counties that are in non-attainment for CO, O_3, PM_{10}, or $PM_{2.5}$ will have lower overall passing rates for body composition testing after adjusting for key demographic variables.

Specific Aim 4: For those criteria pollutants for which an association with aerobic capacity exists after adjustment for demographic factors, determine if there is a dose-response type relationship within counties with non-attainment status.

Hypothesis 6: As the number of air quality exceedances or average concentration for a given pollutant increases, the overall passing rate of schools for aerobic capacity testing will decrease.

1.2 Significance of the Study

A further understanding of the relationship between levels of criteria air pollutants and the physical fitness of children has significant implications. Reports indicate that overall student health is on the decline and that childhood obesity is currently one of the most significant public health concerns in the United States (Ogden et al., 2006). To date, there is no clear consensus regarding the effects of ambient air pollution on athletic performance and physical fitness. However, criteria air pollutants have been associated with health effects (e.g., asthma, respiratory impairment) that would certainly be expected to result in reduced athletic performance.

Decreases in athletic performance and increased body fat levels in children could be predictive of the potential for adult illnesses, such as cardiovascular disease (CVD), morbidity and mortality from Type II diabetes, and other chronic ailments (Eisenmann et al., 2005; Ortega et al., 2005; Velasquex-Mieyer et al., 2005).

1.3 Definition of Terms

For the purpose of this study, key terms are defined as:

Physical Fitness Testing (PFT): A criterion based assessment of measures of physical fitness.

Aerobic Capacity: This term, also referred to as VO_2max, reflects the maximum rate that oxygen can be taken up and utilized by the body during exercise (Welk and Meredith, 2008).

Body Composition: This term refers to the overall percentage of fat measured as a parameter in the physical fitness testing program (Welk and Meredith, 2008).

Criteria Air Pollutants: Criteria air pollutants consist of the six most common air pollutants in the United States: ozone (O_3), carbon monoxide (CO), nitrogen dioxide (NO_x), sulfur dioxide (SO_2), lead (Pb), and particulate matter (PM_{10} and $PM_{2.5}$)

Health Fitness Zone (HFZ): A score in the HFZ represents a "passing" score for the fitness measure being evaluated. The criteria for the HFZ have been based on levels of fitness that can be reasonably attained by most children who participate regularly in various types of physical activity (Welk and Meredith, 2008).

Attainment Area: An area is designated as an attainment area if it meets the National Ambient Air Quality Standards for a given criteria pollutant.

Nonattainment Area: An area is designated as a non-attainment area if it fails to meet the National Ambient Air Quality Standards for a given criteria pollutant.

1.4 Assumptions

Several assumptions are important to this study, as follows:

- It is assumed that the children attending a specific school reside within the county where the school is located.
- It is assumed that ambient air data within the county are representative of exposure at schools located within that county.

1.5 Strengths

- There is a large study population available, as testing is mandatory for California public schools.
- There is an extensive air monitoring network in California.
- This study will consider potential confounders such as socio-economic status.
- This study focuses on examining effects of ambient air pollution on a susceptible sub-population.
- This study will consider the effects of age, gender and ethnicity.

1.6 Limitations

- The study is based on summary statistics of physical fitness testing. Data are aggregated at the grade level within a school and not at the individual child level.
- The study is not designed to determine causality. Significant findings cannot be assumed to be causal without further experimental study.
- It is possible that children may be misclassified as to exposure.
- There is no ability to control for several factors that may influence physical fitness, including nutritional status, genetic factors, and exposure to second-hand smoke.

- There is no way to control for exposures to additional environmental pollutant source contributions.

1.7 Report Organization

Chapter I – The first chapter provides an overview of the research questions and summarizes the significance of this study as well as the strengths and limitations of the research.

Chapter II – The second chapter provides an overview of relevant literature on criteria air pollutants and their effects on physical fitness.

Chapter III – The third chapter presents the methodology and design utilized to conduct this study. This section includes a summary of data collection procedures and the statistical methods used to analyze the data.

Chapter IV – The fourth chapter consists of results of statistical analyses to answer the research questions. Instrument reliability will be addressed and descriptive statistics will be presented. The final section of the chapter is structured to answer the research questions.

Chapter V – The final chapter provides preliminary conclusions and a summary of the study. Contributions to the field and implications for theory and practice as well as future recommendations will be addressed.

Chapter VI – This section is the bibliography for the dissertation.

CHAPTER II

REVIEW OF LITERATURE

2.1 Ambient Air Pollution in the United States

Overview

The U.S. Environmental Protection Agency (EPA) defines an air pollutant as "any substance in the air that can cause harm to humans or the environment" (USEPA, 2009a). Pollutants may be in the form of solid particles, liquid droplets or gases, and may be derived from both natural and anthropogenic (man-made) sources. Release of pollutants into ambient (outdoor) air can result in concentrations that may be harmful to human health and the environment.

The Clean Air Act of 1970 (Pub L No. 91–604) required the EPA to establish National Ambient Air Quality Standards (NAAQS). These enforceable standards (Table 2.1) were set for a group of substances known as 'criteria air pollutants' because they are common, widespread, and known to be harmful to public health and the environment. Criteria air pollutants consist of the six most common ambient air pollutants in the United States: ozone (O_3), carbon monoxide (CO), nitrogen dioxide (NO_x), sulfur dioxide (SO_2), lead (Pb), and particulate matter (PM_{10} and $PM_{2.5}$). Section 109 of the Clean Air Act requires that these standards be reviewed on a five year basis and developed to protect the health of even the most "sensitive" members of a population, such as asthmatics, children, and the elderly (USEPA, 2006).

Individual air pollutant concentrations within areas of the United States (e.g., cities, counties, states) must not exceed the concentrations established as NAAQS. If the levels of these pollutants are higher than their corresponding NAAQS, then the area in which the level is too high is called a nonattainment area, and additional control measures are often necessary.

Table 2.1 – National Ambient Air Quality Standards

	Primary Standards (USEPA, 2009a)	
Pollutant	**Level**	**Averaging Time**
Ozone	0.075 ppm [a]	8-hour
	0.08 ppm [b]	8-hour
	0.12 ppm	1-hour
Carbon Monoxide	9 ppm (10 mg/m^3)	8-hour
	35 ppm (40 mg/m^3)	1-hour
Nitrogen Dioxide	0.053 ppm (100 $\mu g/m^3$)	Annual (Arithmetic Mean)
Sulfur Dioxide	0.03 ppm	Annual (Arithmetic Mean)
	0.14 ppm	24-hour
Lead	0.15 $\mu g/m^3$	Rolling 3-Month Average
	1.5 $\mu g/m^3$	Quarterly Average
Particulate Matter (PM10)	150 $\mu g/m^3$	24-hour
Particulate Matter (PM2.5)	15.0 $\mu g/m^3$	Annual (Arithmetic Mean)
	35 $\mu g/m^3$	24-hour

[a] 2008 ozone standard
[b] 1997 ozone standard

Forty years have passed since the enactment of the 1970 Clean Air Act (Pub L No. 91–604), yet concerns over air quality are still prevalent in the United States. Despite the continuous improvement in overall air quality, as of 2007, 158.5 million people lived in counties that exceeded one or more of the national ambient air quality standards for the six criteria air pollutants (USEPA, 2008).

Sources and General Health Effects

Exposure to criteria air pollutants has been associated with significant effects on human health. Reported short-term effects of exposure to air pollutants include shortness of breath, nausea, headaches, and dizziness. Long-term effects include outcomes such as asthma, chronic bronchitis, kidney failure, central nervous system disorders, birth defects, miscarriage, and cancer (Brook et al., 2004; Florida-James et al., 2004; Simkhovich et al., 2008; Follinsbee, 1993; Carlisle and Sharp, 2001). Health effects from exposure to criteria air pollutants are dependent on the specific pollutant, its concentration, length of exposure, other concurrent exposures, and individual susceptibility (Kampa and Castanas, 2008).

A brief overview describing the sources and health effects associated with each of the individual criteria air pollutants is provided below. A more detailed review that focuses on criteria air pollutants and their impacts on physical fitness is provided in Section 2.6.

Ozone (O_3)

Ozone (O_3) is described as a highly reactive, colorless-to-bluish gas that has a characteristic odor associated with electrical discharges (Brook et al., 2004). Low level exposures to ozone are ubiquitous. Ground level ozone is one of the primary components of photochemical smog, and is a secondary pollutant formed by a chemical reaction between volatile organic compounds (VOCs) and oxides of nitrogen (NO_xs) in the presence of sunlight (Schoenherr, 1992). As such, the formation of ozone tends to be highest on warm, sunny days.

Symptoms associated with elevated exposures to ozone include respiratory irritation, coughing, wheezing, shortness of breath, constriction of the chest, nausea and headaches (Carlisle and Sharp, 2001). Due to its oxidizing properties, inhalation exposure to ozone causes an intense irritation or burning in the delicate tissues that line of the airways of the lung. Reduced lung function can occur, even when the exposure is to low concentrations. Ozone causes aggravation of respiratory and cardiovascular disease and it has been reported that exacerbations of asthma are correlated with ozone levels. Ozone also suppresses the immune defenses of the lungs, making individuals more susceptible to respiratory infections (USEPA, 2008). Animal studies have shown that long-term exposure to high levels of ozone can result in permanent structural changes of the lungs.

Carbon monoxide (CO)

Carbon Monoxide (CO) is an odorless, colorless gas that is generated during the combustion of carbon containing fuels (Brook et al., 2004). Motor vehicles are the most common source of ambient CO emissions; however, emissions may also occur from sources such as wild fires and volcanic eruptions. CO is widely recognized as a poison, with hundreds of people dying from either accidental or intentional exposure each year (Brook et al., 2004).

The toxicity of CO is attributable to its strong affinity for hemoglobin, the oxygen transporting component of red blood cells. CO binds to hemoglobin with an affinity that is 250 times higher than the binding of oxygen with hemoglobin (Brook et al., 2004). This CO/hemoglobin binding complex is referred to as carboxyhemoglobin. Formation of carboxyhemoglobin reduces the amount of hemoglobin available to carry oxygen and also impairs the release of oxygen at the tissue level (Brook et al., 2004).

Nitrogen dioxide (NO_x)

Like carbon monoxide, nitrogen oxides are produced during the combustion of fossil fuels. This group, collectively referred to as "NO_x", includes nitric oxide (NO), nitrogen dioxide (NO_2), nitrogen trioxide (NO_3), nitrogen tetroxide (N_2O_4), and dinitrogen pentoxide (N_2O_3) (Brook et al., 2004).

NO_2 is a regulated air pollutant that reacts with water vapor to form fine acidic droplets and also reacts with volatile organic compounds to generate ground level ozone (Brook et al., 2004; USEPA, 2008). Inhalation of NO_x may lead to aggravation of respiratory disease and an increased susceptibility to respiratory infections (USEPA, 2008; Follinsbee, 1993).

Sulfur dioxide (SO_2)

Sulfur dioxide (SO_2) is a highly irritating, colorless gas that is recognized for its pungent odor and taste (Brook et al., 2004). Ambient SO_2 levels are primarily derived by human activities, such as the combustion of sulfur-containing fuels in power plants (Brook et al., 2004). SO_2 forms sulfurous acid when it comes into contact with water and has a strong irritant effect on the eyes, mucous membranes, and skin surfaces.

Lead (Pb)

Sources of lead in ambient air include smelters and other metal industries, waste incinerators, combustion of leaded gasoline in piston engine aircraft, and battery manufacturing (USEPA, 2008).

Children are much more susceptible to lead toxicity due to their stage of cell development, making their nervous system more vulnerable to inhibition and damage (Patrick, 2006). Children who are exposed to relatively low levels of lead can experience delays in physical and mental development, as well as deficits in attention span, hearing and learning abilities (Patrick, 2006).

Particulate Matter (PM_{10} and $PM_{2.5}$)

Particulate matter (PM) is a complex mixture of suspended particles, varying in both size and chemical composition (Brook et al., 2004). Particulates can be emitted or formed from many sources including chemical reactions (e.g., NO_x, SO_2), fuel combustion, industrial processes, agriculture, and unpaved roads (USEPA, 2008). Generally, these particles consist of inorganic materials, elemental components, biological components, and adsorbed volatile and semi-volatile organic compounds (Simkhovich et al., 2008). Particle sizes, or aerodynamic diameters, of respirable particles range from 2.5-10 um (PM_{10}) for coarse particles, <2.5 um ($PM_{2.5}$) for fine particles, and <0.1 um for ultrafine particles (UFPs) (Simkhovich et al., 2008). These sizes correspond to their ability to penetrate into the respiratory tract. PM_{10} particles are largely deposited in the tracheobronchial tree, whereas $PM_{2.5}$ particles can reach the small airways and alveoli within the lungs (Brook et al., 2004). Ultrafine particles have high rates of deposition into the alveoli, but are unique in that they may be able pass directly into the circulatory system, similar to gases (Brook et al., 2004).

Inhalation of particulate matter can result in the aggravation of respiratory and cardiovascular disease. Particulate matter has also been associated with reduced lung function, increased respiratory symptoms, and premature death (USEPA, 2008).

As seen, each of the criteria air pollutants has been linked to adverse health effects. Complicating the issue, however, is the fact that these chemicals are rarely observed in isolation under real-world conditions. In other words, the ambient environment is comprised of a mixture of multiple gaseous and particulate pollutants. The ratio of these mixtures is variable, both spatially and temporally. According to Follinsbee (1993), these mixtures of pollutants tend to produce health effects that are additive in nature. Individuals living in more heavily populated areas are exposed to these pollutants to a greater extent, due to increased industrialization as well as transportation and energy demands (Kampa and Castanas, 2008).

Air Quality Index

In 1999, the USEPA developed a method to combine concentrations for five of the criteria air pollutants (O_3, PM, CO, SO_2, NO_2) into one measure of overall ambient air quality (AirNow, 2010). This resulting value is called the Air Quality Index, or AQI. Air measurements are converted into a separate AQI value for each pollutant using standard formulas developed by EPA, with the highest of these AQI values being reported as the AQI value for that day.

Values for the AQI run from 0 to 500, with higher values representing higher levels of air pollution and therefore higher levels of health concern. The AQI scale has been divided into six categories (AirNow, 2010), each representing a different level of health concern, as follows:

1) AQI: 0 – 50. **Good.** Air quality is considered satisfactory, and air pollution poses little or no risk.
2) AQI: 51 – 100. **Moderate.** Although air quality is acceptable, some unusually sensitive individuals may have moderate health concerns.
3) AQI: 101 – 150. **Unhealthy for Sensitive Groups.** At this level, the general public is not likely to be affected. However, individuals with lung disease, older adults and children are at greater risk from exposure to ozone, and individuals with heart and lung disease, older adults and children are at greater risk from airborne particulate matter.
4) AQI: 151 – 200. **Unhealthy.** At this level, all individuals may begin to experience adverse health effects. Individuals within sensitive subpopulations may experience more serious effects.
5) AQI: 201 – 300. **Very Unhealthy.** An AQI within these values would trigger a health alert that everyone may experience more serious health effects.
6) AQI: >300. **Hazardous.** These values would trigger emergency conditions health warnings. The entire population is more likely to be affected.

According to the USEPA (AirNow, 2010), an AQI value of 100 generally corresponds to the concentration of the national air quality standard for a pollutant that the USEPA has set to protect public health. AQI values less than 100 are typically considered to be satisfactory. As AQI values exceed 100, air quality is first considered to be unhealthy for certain sensitive groups of people, then for everyone as AQI values increase.

2.2 Ambient Air Pollution in California

When one is asked to consider ambient air quality in California, one of the first images that comes to mind is the heavy smog associated with the metropolitan area of Los Angeles. This photochemical smog largely consists of a complex mixture of nitrogen oxides and hydrocarbons that react in the presence of sunlight to form ozone (Schoenherr, 1992). Ground level ozone and particulate matter emissions have been particularly problematic for California because of the unique characteristics of the state that make it prone to air pollution, including its dense population centers, sunny climate, and topography which can result in the formation of inversion layers.

Air pollution poses a serious health threat in California. According to a report released in 2009 by the American Lung Association (ALA, 2009), several cities in California, including Los Angeles, Bakersfield and Visalla-Porterville, remain some of the most polluted in the U.S., with air quality that is likely damaging the health of millions of people. The state of California reports that over 90 percent of Californians breathe unhealthy levels of one or more air pollutants during some part of the year (State of California, 2009). It has also been reported that "exposure to particulate matter and ozone results in an estimated 8800 premature deaths and 210,000 cases of asthma and other lower respiratory symptoms annually in California" (State of California, 2009).

During the years 2006 and 2007, several California counties were designated as non-attainment for carbon monoxide, 8-hour ozone, PM_{10} and $PM_{2.5}$ (USEPA, 2009b). No counties were in non-attainment for lead, nitrogen dioxide or sulfur dioxide.

In response to the high levels of pollution, the state of California has set many of its own air standards for the criteria air pollutants. These are summarized in the following table.

Table 2.2 – California Ambient Air Quality Standards

	Standards	
Pollutant	**Level**	**Averaging Time**
Ozone	0.07 ppm	8-hour
	0.09 ppm	1-hour
Carbon Monoxide	9 ppm	8-hour
	20 ppm	1-hour
Nitrogen Dioxide	0.030 ppm	Annual (Arithmetic Mean)
	0.18 ppm	1-hour
Sulfur Dioxide	0.25 ppm	24-hour
	0.04 ppm	1-hour
Lead	1.5 $\mu g/m^3$	30-Day Average
Particulate Matter (PM10)	20.0 $\mu g/m^3$	Annual (Arithmetic Mean)
	50 $\mu g/m^3$	24-hour
Particulate Matter (PM2.5)	12.0 $\mu g/m^3$	Annual (Arithmetic Mean)
	No value	24-hour

Source: (California Air Resources Board, 2008)

The California Air Resources Board (ARB) has established the size of the designated areas for criteria air pollutants within the state of California (California Air Resources Board, 2009). These areas vary depending on the pollutant, the location of contributing emission sources, the meteorology, and the topographic features as follows.

- **Air Basin:** is the area designated for ozone, nitrogen dioxide, and particulate matter.
- **County**: is the area designated for carbon monoxide, sulfur dioxide, and lead.

The state of California has a total of 58 counties and 15 air basins. The five most populated air basins are; South Coast, San Francisco Bay Area, San Joaquin Valley, San Diego, and Sacramento Valley (California Air Resources Board, 2009).

Many areas in California have continued to struggle with attainment of air quality standards. The EPA Greenbook (USEPA, 2009b) summarizes the attainment status of California counties from 1992 through 2008. In 2006, four California counties (Los Angeles, Orange, Riverside, and San Bernadino) were designated as non-attainment areas for Carbon Monoxide. No counties were designated as non-attainment in the year 2007. In 2006 and 2007, 35 of 58 California counties were designated as non-attainment areas for the 8-hour Ozone Standard. Fifteen counties were designated as being in non-attainment for PM_{10} during 2006 and 2007, and thirteen counties were designated as non-attainment areas for $PM_{2.5}$ during this same timeframe.

2.3 Susceptibility of Children to Air Pollutants

Potential health impacts to children are of special concern, due to certain physiologic and behavioral characteristics that may make children more susceptible to the effects of pollutants, such as criteria air pollutants.

Physiologic

There are several physiologic differences that contribute to this increased susceptibility. First, the respiratory and neurologic systems of children are not fully developed, causing them to be more vulnerable to adverse health effects (Branis et al., 2008; Kim et al., 2004). Air pollutants have the potential to disrupt the signaling pathways that promote maturation of the lungs (Salvi, 2007). At birth, only 24 million alveoli are present in the lungs. This number increases to 267 million at 4 years of age, and reaches 600 million by adulthood (Trasande and Thurston, 2004 as cited in Salvi, 2007). Impairment of lung growth during childhood can increase the risk for chronic respiratory disease during adulthood (Gilliland et al., 1999).

Likewise, the immune systems of children are immature, providing them with less natural defenses against particulate and gaseous pollutants, and making them more susceptible to respiratory infections (Salvi, 2007). A greater risk of lower-than-normal lung function later in life is a concern for children who experience frequent respiratory infections (ALA, 2000).

Children have a higher breathing rate than adults relative to their body weight and lung surface area (ALA, 2000; Salvi, 2007). This physiological difference results in a greater dose of pollution being delivered to the lungs of a child under similar exposure conditions. For example, when adjusted for body weight, the total air volume passing through the lungs of a resting infant is two times higher than that of a resting adult (Salvi, 2007). This can have significant implications on the development of adverse outcomes as the majority of biological damage attributable to air pollution is associated with the total dose of pollutant inhaled in relation to the body weight and surface area of the target organ. Physiologically, children have narrower airways than adults (Salvi, 2007). Consequently, irritation or inflammation caused by air pollution that would generate only a slight response in adults can result in potentially significant obstructions in the airways of children (ALA, 2000).

Behavioral

Children are outdoors a great deal more than adults, especially in the summertime and late afternoons when ozone levels are the highest (Salvi, 2007). Some of this outdoor time is spent engaged in active play, which increases breathing rates and overall exposure to ambient air pollutants (Kim et al., 2004). A California study reported that children were found to spend three times as much time engaged in sports and vigorous activities as were adults (ALA, 2000). This increased activity results in children subsequently breathing in larger air volumes (Branis et al., 2008). The heavier breathing rates that accompany exercise result in more pollution being delivered into the deeper portions of the lungs. It has been reported that there is a five-fold increase in the deposition of particles into the lungs during exercise as compared to rest (Salvi, 2007). This increased rate of deposition is explained by not only the increased breathing rate associated with exercise, but also how the breathing occurs. When breathing rates become heavier, children, like adults, use both their noses and mouths to breathe, rather than just their noses. When the mouth is used during the breathing, the filtering effects of the nose are lost, therefore allowing more air pollution to reach the lungs. (ALA, 2000)

Compared with adults, children are less likely to report exposure-related symptoms (Gilliland et al., 1999; Reigart et al., 1993). This indicates that they may not perceive significant drops in lung function well or may not experience the same amount of coughing, wheezing or shortness of breath (e.g., associated with ozone exposure) as is seen in adults. This could result in children not self-limiting their activities and thereby having greater exposures to air pollution.

2.4 Physical Fitness in the United States

Overview

Public interest in children's health and fitness skyrocketed during the 1950's when it was reported that American children were less fit than European children (Pivarnik and Pfeiffer, 2002). This finding ultimately led President Eisenhower, in 1956, to establish the President's Council on Youth Fitness with the focus of promoting active lifestyles (Wargo, 2007). Under President Kennedy the subject of physical fitness remained in the spotlight, and this agency was renamed the President's Council on Physical Fitness and Sports (Pivarnik and Pfeiffer, 2002).

Early fitness testing focused on evaluations of general motor performance skills such as muscular strength, speed and power (Pivarnik and Pfeiffer, 2002). As this field has progressed, the focus has shifted away from the traditional motor skills evaluation to a more health-related assessment. Today's fitness tests often include measures of aerobic fitness and obesity. Additionally, many of the current tests are criterion referenced, so that individual results can be evaluated in terms of overall health, rather than simply compared to the test population as a whole (Pivarnik and Pfeiffer, 2002).

Trends in Physical Fitness

Despite the focus on physical fitness in youth, trends in this area are disturbing. The Centers for Disease Control and Prevention have reported that the majority of children in the United States do not get sufficient physical activity, with one-third of all children being considered inactive (The California Endowment, 2005). Excess weight in children has been referred to as the "fastest growing, most threatening disease in America" (CMA Foundation, 2008) and continues to be a leading public health concern. The Centers for Disease Control and Prevention (CDC) report that the percentage of overweight children aged 6-11 years has almost doubled since the early 1980's, whereas the percentage of overweight adolescents has nearly tripled. Ogden et al. (2006) report that in 2003-2004, a total of 17.1% of children and adolescents in the United States were determined to be overweight.

According to The California Endowment (2005), one in three children (~33%) in California is considered overweight, and four out of every ten children are estimated to be unfit. In certain California school districts, half of the children have been determined to be overweight (The California Endowment, 2005). This overweight and inactive status is likely to follow these children into adulthood.

It has been reported that California is experiencing the fastest increase in adult obesity in the nation (CMA Foundation, 2008). The price tag associated with obesity comes in at a direct and indirect cost of $100 billion per year nationally. In California alone, this figure is $28.5 billion (CMA Foundation, 2008). The early establishment of positive exercise habits in childhood can carry into adulthood helping to reduce cardiovascular disease, morbidity and mortality from Type II diabetes, and other chronic ailments (Eisenmann et al., 2005; Ortega et al., 2005; Velasquex-Mieyer et al., 2005).

Factors That may Influence Physical Fitness in Children

There are numerous factors that can potentially influence measures of physical fitness in children. These factors include diet, socio-economic status (SES), ethnicity, gender, body weight, parents' education level, maturation, chronological age, genetic factors, handicaps/physical limitations, and ambient air pollution.

Ogden et al. (2006), in a summary of the prevalence of overweight and obesity in the United States from 1999 to 2004, show an increase in the risk of overweight as ages increase in children. After adjusting for age, the authors found that significant differences between racial/ethnic groups persisted. The prevalence of overweight status in Mexican-American male children was significantly higher than that in non-Hispanic White male children. In addition, Ogden et al. (2006) found that Mexican-American and Black (non-Hispanic) female children were significantly more likely to be overweight than White (non-Hispanic) female children. McMurray et al. (2000) reported that ethnicity and SES may be important influences on body weight status. In addition to noting that female adolescents with low SES were more likely to be overweight, they noted that being White and having a high SES reduced the overall risk of being overweight. Powell et al. (2009) found a significant increase in the body mass index of Black and Hispanic students from Georgia as compared to Whites.

In a study evaluating the physical fitness of children in Los Angeles, Lee et al. (2006) found a significantly higher prevalence of overweight among boys than girls. In addition, they found that the prevalence of overweight was inversely related to grade level and socio-economic status. Powell et al. (2009) found that male students in Georgia had significantly higher percentages of students below the healthy fitness level for body mass index than females.

In a review of the current fitness literature, Park and Kim (2008) found evidence of associations between physical activity and age, gender, parental education level, SES, and several other test variables. Several studies cited in this report found inverse associations between age and physical activity, thus implying that performance on physical fitness testing may also vary by age. Males were reported as being more physically active than females. High parental education levels and high socio-economic levels were found to have positive associations with physical activity levels in adolescents. Drewnowksi et al. (2008) report that poverty was significantly associated with overweight status in children residing in California Assembly districts.

Children of the same age can vary in their level of physical maturity or motor development. Physical maturity level may be an important variable in physical fitness performance. Boys who lack physical maturity may appear weaker than their more physically mature counterparts, whereas girls who have increased physical maturity may also have higher levels of stored body fat. Children with advanced physical maturity may have distinct advantages when strength and power are being evaluated. Alternately, children with physical handicaps or other limitations may perform more poorly on standard fitness testing.

Body composition itself can play a role in physical fitness performance. Norman et al. (2005) investigated the influence of excess body fat on exercise fitness and performance in children. The authors found that overall cardiorespiratory fitness was similar; however, functional impairment was associated with increased energy demands attributable to the excess body weight. Drinkard et al. (2001) found walk/run distances in obese study participants to be substantially less than for non-obese individuals. Thus, obesity may influence the performance on aerobic fitness testing.

Genetic factors may also play a role in physical fitness. A study by Maes et al. (1997) reports that an estimated 50-90% of the variance in body mass index may be attributable to genetic factors. In addition, genetic factors/heredity can lead to various physical maturation and body type outcomes.

Tsimeas et al. (2005) investigated the effect of fatness in rural or urban settings on physical fitness in children. They concluded that place of residence had no clear impact on overall physical fitness.

Air pollution, the key focus of this study, has also been linked to adverse health effects that may have an impact on overall physical fitness in children. Further discussion of these health effects associated with ambient criteria air pollutants are provided in Section 2.6.

2.5 Physical Fitness Testing (PFT) in California

Overview of PFT

The California statewide physical fitness testing program was first authorized in 1976. The program was reestablished in 1995 under the California Assessment of Academic Achievement Act. This act (Assembly Bill [AB] 265) added Education Code Section 60800, which mandates the schools to administer the physical fitness testing. In February 1996, the State Board of Education designated FITNESSGRAM®, a test developed by the Cooper Institute, as the required test for administration.

Each spring, all school districts within California are required to administer this state-designated Physical Fitness Test (PFT) to all students in fifth, seventh and ninth grades. This assessment occurs each calendar year during a window of time spanning from February 1 through May 31. Six different fitness areas are assessed within this program. These are described in further detail below. The fitness standards established within FITNESSGRAM are based on a criterion-referenced, health-related approach. Results from the testing are submitted to the California Department of Education (CDE), which provides aggregate results to the school districts and maintains a publicly accessible database of test results on its Web site.

Testing Criteria

The FITNESSGRAM® test utilized for the California Physical Fitness Testing program is composed of the following six fitness areas:

1) Aerobic Capacity

2) Body Composition

3) Abdominal Strength and Endurance

4) Trunk Extensor Strength

5) Upper Body Strength and Endurance

6) Flexibility

Most of these have multiple tests by which fitness may be measured. These tests and their associated performance criteria are summarized in Table 3 and discussed in further detail below.

Figure 2.1 – California Measures of Physical Fitness

California Physical Fitness Test (PFT)
***FITNESSGRAM®*: Fitness Areas, Test Options, and Equipment**

Fitness Areas					
Aerobic Capacity	Body Composition	Muscular Strength, Endurance, and Flexibility			
		Abdominal Strength and Endurance	Trunk Extensor Strength and Endurance	Upper Body Strength and Endurance	Flexibility
Test Options					
■ PACER* (Progressive Aerobic Cardiovascular Endurance Run) • Flat, nonslippery surface 15 or 20 meters in length • CD or cassette player with adequate volume • CD or audiocassette with music/timing • Measuring tape • Marker cones ■ One-Mile Run • Flat, measured running course • Stopwatch ■ Walk Test • Flat, measured course • Stopwatch	■ Skinfold Measurements* • Skinfold caliper ■ Body Mass Index • Scale • Ruler (stadiometer) or tape measure ■ Percent Body Fat • Bioelectric impedance analyzer or automated skinfold caliper • Scale • Ruler (stadiometer) or tape measure	■ Curl-Up* • Gym mat • 3 inch (5 to 9 year olds) or 4.5 inch (all older students) measuring strip • CD or cassette player with adequate volume • CD or audiocassette with cadence	■ Trunk Lift* • Gym mat • Yard stick or 15-inch ruler	■ Push-Up* • Gym mat • CD or cassette player with adequate volume • CD or audiocassette with cadence ■ Modified Pull-Up • Gym mat • Modified pull-up stand with elastic band ■ Flexed-Arm Hang • Horizontal bar • Chair or stool • Stopwatch	■ Back-Saver Sit and Reach* • Sit-and-reach box ■ Shoulder Stretch

All of the test options require pencils and score sheets to record scores.
**FITNESSGRAM®* recommends this test as the test option for the fitness area; however, the California Department of Education (CDE) does not have a position regarding the use of specific test options.

Source: (California Dept. of Education, 2010)

Aerobic Capacity: Aerobic capacity (VO_2max) describes the maximum rate at which oxygen can be taken up and utilized by the body during exercise. There are numerous terms that have been used to describe this particular aspect of physical fitness, including: cardiovascular fitness, aerobic fitness, aerobic work capacity, cardiorespiratory fitness, cardiorespiratory endurance, and physical working capacity (Meredith, 2008). Although these terms have slight differences in definition, they are generally considered to be synonymous with aerobic capacity.

There are three field tests specified by the FITNESSGRAM testing program to assess aerobic capacity: the PACER (Progressive Aerobic Cardiovascular Endurance Run), the one-mile run, and a walk test (for adolescents 13 years of age or older) (Welk and Meredith, 2008). The first two tests estimate aerobic capacity based on running performance and participant characteristics such as age, gender, body weight and the ratio of weight to height, whereas the third test estimates aerobic capacity from heart rate response to a one-mile walk and selected subject characteristics (Welk and Meredith, 2008). Although the PACER test is the recommended test to assess aerobic capacity, the California Department of Education does not have a position as to which specific testing protocol should be utilized. More details on these testing protocols can be obtained in Meredith (2008) and Welk and Meredith (2008).

Body Composition: Body Composition, as evaluated in the FITNESSGRAM testing protocol, is a measure of the percentage of body fat. Two evaluative methods, skinfolds and body mass index, have been identified. Skinfold measurements are the preferred field method for evaluating this parameter. The measurement of skinfolds from both the triceps and calf can be effectively used to estimate the percentage of body fat in children of all ages (Welk and Meredith, 2008). Skinfolds are a highly reliable field method for estimating body fatness with reported standard errors of 3 to 4 % body fat (Welk and Meredith, 2008). The second method, called body mass index or BMI, evaluates body fattness based on height and weight measurements. However, the prediction error associated with BMI is greater (5.6%) than that for skinfolds (Welk and Meredith, 2008**).** Therefore, this approach is not considered as effective in identifying children who are only moderately overfat (Welk and Meredith, 2008**).**

The criteria for body composition were derived using nationally representative data from the early NHANES surveys stratified by age and gender. Based on this data, the FITNESSGRAM Health Fitness Zone standards for body composition are 25% fat for boys and 32% fat for girls (Meredith, 2008)

Muscular Strength, Endurance and Flexibility: Muscular strength, endurance and flexibility are considered to be important aspects of health-related fitness. Musculoskeletal fitness has been shown to have a positive relationship with various health status indicators, including risk factors, disease development and all-cause mortality in adults (Meredith, 2008). According to Meredith (2008), the musculoskeletal system is dependent on three elements in order to be viewed as a balanced, health-functioning system: 1) muscles should be able to exert force or torque (strength), 2) the muscular system should resist fatigue (endurance), and 3) muscles should move freely through a full range of motion (flexibility). There are four categories of muscular strength, endurance and flexibility testing used by FITNESSGRAM. These are: Abdominal Strength and Endurance, Trunk Extensor Strength, Upper Body Strength and Endurance, and Flexibility. Although these tests measure important aspects of fitness, no specific measurement criterion has been identified. Further details of each test are provided below.

<u>Abdominal Strength and Endurance:</u> FITNESSGRAM recommends a cadence-based curl-up test for the evaluation of abdominal strength and endurance (Welk and Meredith, 2008). The use of a 3-second pace helps to avoid early fatigue, standardizes the movement from person to person, and facilitates judging as to whether a full proper repetition has been completed (Welk and Meredith, 2008).

<u>Trunk Extensor Strength and Flexibility:</u> FITNESSGRAM utilizes a trunk lift as a measure of both lumbar flexibility and trunk extensor strength (Welk and Meredith, 2008). Insufficient trunk extension strength/endurance is predictive of both first time and recurrent low back pain (Welk and Meredith, 2008).

Upper Body Strength and Endurance: FITNESSGRAM recommends use of the 90^{o} push-up at a cadence of one per every three seconds, in order to measure upper arm and shoulder girdle strength as well as muscular endurance. The modified pull-up and flexed arm hang are optional items (Welk and Meredith, 2008).

Flexibility: FITNESSGRAM recommends the Back-Saver Sit and Reach Test for assessing lower body flexibility. The shoulder stretch has been added as an alternative evaluation method (Welk and Meredith, 2008).

2.6 Criteria Air Pollutants and Relationship with Measures of Physical Fitness

There is no question that criteria air pollutants are associated with adverse impacts on respiratory health. This finding has been documented in hundreds, if not thousands, of scientific papers and summaries of these papers are not presented within this report. This report focuses on those studies that are associated with more specific measures of physical fitness or those that are specific to children's health.

Few studies have examined the association of ambient air pollution with athletic performance, and fewer have examined the relationship of pollution and fitness among school-aged children. To elucidate the potential relationship between air pollution and adverse health outcomes, two sources of information are often utilized: 1) laboratory animal studies, and 2) human epidemiology investigations.

Laboratory Animal Studies

Measures of fitness are more often studied in human populations than in animals; therefore, the associated body of literature is relatively small. No animal studies were found linking cardiovascular fitness (aerobic capacity), muscular strength or flexibility to criteria air pollutants.

Recently, a possible link has been made between ambient air pollution and diet-induced obesity in mice. Sun et al. (2009) reported that exposure to air pollution, over a period of 24 weeks, exaggerates insulin resistance and fat inflammation. Male C57BL/6 mice were fed a diet high in fat over a 10-week period to induce obesity and then subsequently exposed to either filtered air or air with particulate matter ($PM_{2.5}$) for six hours a day, five days a week, over a 24-week period. The air pollution level inside the chamber containing particulate matter was comparable to levels a commuter may be exposed to in urban including many metropolitan areas in the United States. Researchers monitored measures of obesity, fat content, vascular responses and diabetic state. Increases in visceral and mesenteric adipose mass were observed in mice exposed to air containing $PM_{2.5}$. The tests showed that in combination with a poor diet, air pollution caused increased body fat and interfered with insulin processing.

<u>Human Studies</u>

There are numerous human studies that have evaluated associations between criteria air pollutants and measures of physical fitness. This section summarizes some of the key studies for both children and adults.

Children

In 1967, Wayne et al. (cited in Folinsbee, 1992) reported an inverse relationship between the seasonal improvement in the race times of high school cross-county runners and ambient ozone concentrations.

Gauderman et al. (2004) conducted a prospective study in which the lung function of 1,759 children (~10 years old) from 12 communities in southern California was evaluated over an 8-year period. Linear regression was used to evaluate the relationship between air pollutants (ozone, acid vapor, nitrogen dioxide and particulate matter) and growth in FEV1 (forced expiratory volume in one second). The researchers found that deficits in FEV_1 were associated with exposure to nitrogen dioxide and $PM_{2.5}$. The authors concluded that these results indicate that current levels of air pollution have chronic, adverse effects on lung development in children (Gauderman et al, 2004).

Calderón-Garcidueñas et al. (2006) evaluated the respiratory health of children from Tlaxcala versus children from the more heavily polluted region of southwest Mexico City. According to the authors, children from southwest Mexico City are chronically exposed to both ozone and $PM_{2.5}$ concentrations exceeding levels established as U.S. National Ambient Air Quality Standards. Chest radiographs for 19 children from Tlaxcala and 230 children from southwest Mexico City were analyzed, with hyperinflation and interstitial markings found to be significantly more common in children from Mexico City ($p<0.0002$ and 0.00006 respectively).

Chen et al. (1999) evaluated the short-term effect of ambient air pollution on the pulmonary function of schoolchildren. A total of 941 primary school students from three communities in Taiwan (Sanchun, Taihsi, and Linyuan) were selected for evaluation. Hourly ambient concentrations of sulfur dioxide, carbon monoxide, ozone, PM_{10}, and nitrogen dioxide were obtained via the Taiwan air quality monitoring network. The authors used multivariate linear regression to evaluate pulmonary function effects (measured via spirometry) of each pollutant in addition to determinants of indoor air pollution and meteorological conditions. Study findings included a significantly negative association of peak ozone concentration on the day before spirometry testing with individual forced vital capacity and forced expiratory volume in 1 sec.

Jedrychowski et al. (1999) investigated the effect of low concentrations of ambient air pollution on lung function growth in preadolescent children. The study was conducted in 1,001 preadolescent children from two areas of Krakow, Poland, that differed in concentrations of ambient air pollutants. The authors found that lung growth in these children was affected even at a relatively low air pollution level. For boys and girls living in the more polluted area of the city, the adjusted mean lung function growth rate over the 2-year follow-up period was significantly lower.

Rodriguez et al. (2007) evaluated the relationship between concentrations of air pollutants and respiratory symptoms in young Australian children. A total of 263 children, age 5 and under, were recruited and followed over a period of 5 years. These children were selected for their higher familial risk of developing asthma or atopy (allergic hypersensitivity). Respiratory symptoms were recorded during the course of the study by each child's parents. Meteorological data and pollutant concentrations were collected from network monitoring sites. Logistic regression models were utilized to assess relationships between individual air pollutants and respiratory symptoms. The authors observed significant associations between ozone (1 hour and 8 hour) concentrations and raised body temperature; Carbon monoxide (8 hour) and wheeze/rattle and runny/blocked nose; Nitrogen dioxide (24 hour) and cough; and $PM_{2.5}$ and cough. The air pollutant concentrations were below national standards throughout the course of the study.

Frye et al. (2003) evaluated the effects of improved air quality on lung function in East German school children. Consecutive cross-sectional surveys of children aged 11-14 from three communities were conducted in 1992–1993, 1995–1996, and 1998–1999. Lung function tests were evaluated for a total of 2,493 children. Annual mean concentrations of total suspended particulates (TSP) between 1991 and 1998 decreased from 79 to 25 $\mu g/m^3$, and concentrations of sulfur dioxide decreased from 113 to 6 $\mu g/m^3$. The authors found that the mean forced vital capacity (FVC) and forced expiratory volume in 1 sec (FEV_1) of the children was increased from 1992–1993 to 1998–1999. For a 50 $\mu g/m^3$ decrease in TSP, the adjusted percent change of the geometric mean of FVC was 4.7% ($p = 0.043$). This percent change was 4.9% for a decrement of 100 $\mu g/m^3$ SO_2 ($p = 0.029$). FEV_1 appeared to improve with decreasing air pollutions, but the effects were smaller and not statistically significant.

Lippmann (1989) conducted a series of field studies that evaluated populations of children at summer camp, who were exposed to ozone at concentrations below the then National Ambient Air Quality standard of 120 ppb for a 1-hour averaging time. These children were exposed for extended durations to outdoor air while engaged in supervised camp activities. Significant decrements in function were observed as measured by forced expiratory volume in 1-second (FEV_1), forced vital capacity (FVC), peak expiratory flow rate (PEFR), and forced expiratory flow between 75 and 25% of vital capacity (FEF_{25-75}). Lipmann (1989) also summarizes findings from a study of 91 children in 1984, which found significant ozone associated decrements in lung function for environmental exposures truncated above both 80 and 60 ppb.

Kinney et al. (1996) reanalyzed data from 6 summer camp studies in order to assess the effects of ambient ozone on lung function in children. All six studies found an inverse relationship between ozone and forced expiratory volume, with FEV_1 decreasing as ozone concentrations increased. This relationship was significant in five of the six studies. The combined data set yielded a significant ($p<0.0001$) reduction in FEV1 of -0.50 ml per each one ppb increase in 1-hour O_3 concentration.

Lin et al. (2008) reported a positive dose-response relationship between chronic exposure to ambient concentrations of ozone and asthma hospital admissions in children. Stronger associations were observed in younger children, lower SES status, and New York City residents.

Hong et al. (2007) found that exposures to metals in particulate pollutants as well as $PM_{2.5}$ were associated with decreased peak expiratory flow rates (PEFR) in schoolchildren. Forty-three Korean children in 3rd through 6th grade were evaluated during 2004. Using a 1-day lag model, significant decreases in PEFR were observed after adjusting for age, sex, height, weight, asthma history, passive smoking exposure, meteorologic variables, and day of the week following exposure to $PM_{2.5}$. The mean decrease was estimated at -0.54L/min per 1 ug/m^3 $PM_{2.5}$.

Adults

Galizia and Kinney (1999) evaluated the respiratory health of 520 Yale college students, aged 17-21, in regards to their long-term ozone exposure histories. A high ozone exposure category was assigned to 65 of the participants based on their history of residing for a minimum of four years in a United States county with a 10-year average summer-season daily 1-hour maximum concentration of ozone $\geq$ 80 ppb. After controlling for confounding variables (race, gender, body size, SES, and indoor environmental factors), the high exposure group was observed to have significantly diminished lung function (FEV_1 and FEF_{25-75}) and elevated chronic respiratory symptoms.

A study of lung function in young males after inhalation of ultrafine and fine particulate matter during exercise was conducted by Rundell et al. (2008). Twelve physically fit, non-asthmatic, nonsmoking males (average age = 20.5), performed two random-order exercise activities while breathing either low ambient PM_1 or high ambient PM_1. Exercise trials required running for 30 minutes at 85-90% of maximal heart rate. The authors determined that the men experienced post-exercise changes in lung function that were significantly related to the PM_1 concentration. Although no clinically significant decreases in lung function were noted, for every increase of 20,000 particles per cubic centimeter, statistically significant decreases of 11.1 ml in FEV_1 and 52 ml in FEF_{25-75} were observed after 30 minutes of exercise.

Girardot et al. (2006) investigated the pulmonary health effects of ozone and $PM_{2.5}$ on recreational visitors to the Great Smoky Mountains National Park. The authors conducted an observational study of adult (18-82 years of age) day hikers of the Charlies Bunion trail during fall 2002 and summer 2003. Pre- and post-hike pulmonary function tests (spirometry) were administered to volunteer hikers. Ambient ozone, $PM_{2.5}$, temperature, and relative humidity levels were continuously monitored at the trailhead. No significant change in forced vital capacity (FVC), forced expiratory volume in 1 sec (FEV_1), FVC/FEV_1, peak expiratory flow, and mean flow rate between 25 and 75% of the FVC was found when these data were regressed each separately against pollutant (ozone or $PM_{2.5}$) concentration and adjusted for various factors. Measured ozone and $PM_{2.5}$ concentrations were below the federal standards.

Kippelen et al. (2005) followed healthy endurance athletes in the Mediterranean region to determine if any functional airway changes occurred during the course of the sports season. Respiratory function, before and after exercise, and ventilatory response to exercise were analyzed in 13 athletes three times during the year. The authors noted that during the competitive period, a slight but non-clinically significant decrease was found in forced vital capacity (23.5%, $p = 0.0001$) was found. There was no concomitant reduction in expiratory flow rates. Overall, this study does not provide significant evidence of lung function impairment in healthy Mediterranean athletes following one year of endurance training.

Foxcroft and Adams (1986) exposed eight exercising male study participants to 1-hour concentrations of 0.35 ppm ozone on 4 consecutive days. Each subject was evaluated for VO2max, performance time, pulmonary function, and subjective symptom responses. Although reported symptoms had decreased by the fourth day of exposure, pulmonary function impairment persisted with a significant decrease over that observed from exposure to filtered air.

Adir et al. (1999) investigated the effects of exposure to low levels of carbon monoxide on exercise performance in young healthy men. In this two stage study, fifteen, non-smoking, healthy men were exposed to either room air, or a mixture of CO and room air on a randomized basis. One month later, each subject was assigned to the alternate exposure group. Therefore, subjects served as their own controls. The CO exposure was designed to produce a venous blood carboxyhemoglobin (COHb) concentration of 4-6%, thought to be representative of levels observed in individuals living in industrial and inner city areas. Immediately following exposure, subjects performed an exercise treadmill test at maximal capacity until exhaustion was reached. In 13 of the 15 subjects exposed to CO and room air, their effort was maintained for a shorter duration than after exposure to room air alone. In addition, all subjects demonstrated a lower degree of overall maximal effort, as measured by metabolic equivalent units, after carbon monoxide exposure.

Marr and Ely (2009) investigated the effect of air pollution on marathon running performances. The investigators evaluated marathon race results, weather data, and concentrations of criteria air pollutants for seven marathons over the course of 8 to 28 years. The top three male and female finishing times for each marathon and year were compared to the corresponding environmental information. The air pollutants concentrations over the study timeframe ranged from 0-5.9 ppm for carbon monoxide, 0-0.7 ppm for ozone, 4.5-41 ug/m^3 for PM_{10}, and 2.8-42 ug/m^3 for $PM_{2.5}$. Although it was determined that the concentrations of air pollutants present during each marathon were typically below relevant health based standard, PM_{10} was found to be significantly correlated with the performance of female marathon runners. Marr and Ely (2009) found that for each 10 ug/m^3 increase in PM_{10}, there was an associated decrease in finishing time of 1.4%.

Rundell (2004) investigated the effects on pulmonary function in 14 female ice hockey players exposed to ultrafine and fine particulate matter (PM_1) released from fossil fueled ice resurfacing machines. Controls consisted of nine female Nordic skiers. Athletes were followed over a period of four years and evaluations of lung function, asthma symptoms and PM_1 exposure were made. Particle counts from the fossil fueled equipment were 13-fold higher than that observed from the electric-powered equipment. No significant changes in lung function were observed for controls, whereas the female hockey players demonstrated decrements in lung function. Although the study population was small, the authors suggest that daily exposure to high PM_1 may result in a decay of airway function with rates of decline exceeding those documented for asthmatics.

2.7 Chapter Summary

This chapter provided a review of the available literature on criteria air pollutants and their association with measures of physical fitness in children. Air pollution is of special concern in California as areas within the state continue to struggle with attainment of air quality standards. The health effects associated with criteria air pollutants are varied. However, many of these effects impact respiratory health and one recent study has reported an association between air pollution and body fat in mice. As shown in this chapter, children are a susceptible sub-population to the adverse health effects of air pollution. The public availability of results from mandatory physical fitness testing programs for school children in California offers the ability to combine datasets on air pollutants with those containing physical fitness testing results to determine if a relationship exists.

CHAPTER III

METHODOLOGY

The purpose of this study is to determine if a relationship exists between ambient air pollutants and physical fitness in children. Data from physical fitness testing will be evaluated to determine whether areas with higher pollutant concentrations have decreased physical performance when compared to areas with lower pollutant concentrations.

To help address this research question, the relationship between standardized measures for fitness and concentrations of criteria air pollutants will be evaluated, adjusting for those demographic variables that may influence overall physical fitness. This study aims to determine the relationship between physical fitness during 2006 and 2007, as measured by the mandatory California Physical Fitness Testing Program in fifth-, seventh-, and ninth-grade public school children, and those criteria air pollutants that were in non-attainment in California during this timeframe.

3.1 Measures

Physical Fitness. Physical fitness will be measured using results from the California state Physical Fitness Testing program, known as FITNESSGRAM®. FITNESSGRAM® is a criterion-referenced test that evaluates school children based on six measures of physical fitness. The state of California requires mandatory annual testing of all public school students in the fifth-, seventh-, and ninth-grades.

Results from the Physical Fitness Testing program within the state of California are currently available for a nine year span ranging from 1999 to 2008. These data are publicly available from the California Department of Education (2009a) Web site. For each fitness parameters assessed, the percentage of children in each grade that are determined to be in the “Health Fitness Zone” (acceptable), or “Not in Health Fitness Zone” (unacceptable) are provided. These data are accessible at multiple levels, including by school, district and county.

For this analysis, a Fitness Achievement variable was constructed as the percentage of students within each school, separated by grade, that are determined to pass a specific criteria measure (Health Fitness Zone). Based on the literature review, the two fitness endpoints that were evaluated in this study are aerobic capacity (AerCap) and body composition (BodFat). These variables were used in the statistical models as continuous dependent variables.

Data were restricted to the years 2006 and 2007, as the data collection mechanisms were similar across both of these years. The use of two years of data, rather than one, allowed for evaluation of more grade/school combinations and, therefore, the development of a more robust dataset. Additionally, this two year window avoided the problem of “double-counting” the same participants in the analysis, as would occur if a time period greater than two years was utilized. For example, children in a 5th grade class during 2006, would be reassessed as the 7th grade class in 2008.

Because the California Department of Education does not report aggregate fitness results when a class size is equal to or less than 10 students, the data were restricted to those grades with 10 or more students at each school.

Research files were downloaded and organized using Microsoft Access prior to upload of specific datasets into the statistical software.

Sociodemographic Measures. Aggregate data on gender (male/female) and ethnicity for the study groups were available from the California Department of Education (CDE, 2009a) along with results from the physical fitness testing. For one variable, the number of males in each grade/school combination was converted to the total percentage of males for a grade/school. In a second, a dataset was developed that split the fitness performance results into a dichotomous split of male and female records. This latter variable was used for grouped statistical analyses (e.g., t-test, ANOVA), whereas the variable consisting of the percentage of males per school was used for regression analyses.

Reported ethnicities consisted of African American, American Indian/Alaskan Native, Filipino/Filipino American, Hispanic/Latino, White, Asian, and Pacific Islanders. In addition to the separate ethnicity records, a variable was created to reflect the total percentage of minorities (percent non-White) for each grade/school combination.

Numeric values for the grade being evaluated (5, 7 or 9) were used as surrogates for the age of the children in tests to determine if fitness varied by age. These data were obtained from the California Department of Education along with the results of the physical fitness testing.

Data from a separate database within the California Department of Education (CDE, 2009c) on the percent of free or reduced price meals (FRPMs) within a school were used as a surrogate for socio-economic status (SES). These data were available at the individual school level and were matched back to the data set containing physical fitness data for each school. In addition to having a measure reflecting the percent SES at a school, these SES data were also categorized into quartiles for grouped data analyses. Quartile 1 represented 0-25% of the children receiving free or reduced price meals (FRPMs), Quartile 2 was for >25-50% of the children within a school receiving FRPMs, Quartile 3 was for >50-75% of the children within a school receiving FRPMs, and Quartile 4 was used when >75-100% of the children with a school were reported to receive FRPMs.

Body Fat was also included as an independent variable when evaluating Aerobic Capacity as a dependent variable using multiple regression analysis. This variable was obtained as part of the fitness testing results available from the California Department of Education (2009a) Web site. The variable reflects the percentage of students in a grade/school combination that had passing (healthy) body fat scores.

Air Pollution. California has an extensive air quality monitoring program that includes analysis and reporting of concentrations of the criteria air pollutants. Data on the criteria air pollutants in California were obtained from multiple sources.

Attainment Status: The attainment status of each California county during the years 2006 and 2007 was obtained from the USEPA Greenbook (USEPA, 2009b). The Greenbook reports those counties identified as being in non-attainment for a given criteria air pollutant. All unlisted counties were assumed to be in attainment. It was determined that various California counties were in non-attainment for carbon monoxide, 8-hour ozone, PM_{10} and $PM_{2.5}$ during 2006 and 2007. A summary of attainment status by county is provided in Appendix B.

Air Quality Index: The USEPA AirData Web site (USEPA, 2009c) was used to obtain data on the Air Quality Index (AQI) for each California county. A unique variable was created by summing the number of days that the AQI exceed a value of 100. Only counties with 365 days of AQI values in a given year were utilized for this variable. These data were obtained for 2005 and 2006, the years preceding the fitness testing evaluated in this report.

Air Quality Exceedances: There were two variables created for this measure. One represented the number of days that the average concentration of 8-hour Ozone within a county exceeded the NAAQS (0.075 ppm) over the course of a year. The data comprising this variable were obtained from the Web site for the California Environmental Health Investigations Branch (2010). For PM_{10}, the California Environmental Health Investigations Branch (2010) provides the percentage of days that daily PM_{10} average concentrations were over the California Standard of 50 ug/m^3. For consistency, this percentage was converted to the number of days that the standard was exceeded by multiplying the fractional percentage of days per year by a value of 365.

Person Days: Data on person-days were obtained from the California Environmental Health Investigations Branch (2010). Person-days are equivalent to the number of days the pollutant exceeds a health standard times the number of persons living in an exposed region. Person-days offer a representation of the overall population burden of air pollution exposure.

Annual Average Concentration: Annual average concentrations of 8-hour Ozone (ppm) and PM_{10} (ug/m^3) were obtained for each county from the air quality Web site for the California Environmental Health Investigations Branch (2010).

3.2 Data Analysis

The association of criteria air pollutants with measures of aerobic capacity and body composition was evaluated using the statistical software package SPSS 16.0. As discussed above, various publicly accessible databases were accessed and queried for relevant variables. Once extracted, these data were placed into a Microsoft Access database and merged together by either school or county so that statistical analyses could be performed.

Prior to testing the hypotheses outlined in this prospectus, appropriate data screening steps were conducted and summarized, and descriptive statistics were analyzed on each variable.

To assess the association between the fitness status and criteria air pollution, several research questions were identified (Section 1.2). To address these questions, a variety of statistical methods were employed. T-tests were used when two means were compared and ANOVA's were used when more than two means were compared. A series of t-tests were conducted to determine if physical fitness differs between attainment and non-attainment areas. Both t-tests and one-way ANOVA were used to identify explanatory variables. Multivariate regression models were constructed to evaluate the strength of the association between fitness achievement and attainment status after controlling for demographic variables such as gender, SES, grade, and ethnicity. For those pollutants that were found to be significant after controlling for demographic variables, additional multivariate regression analyses were performed to determine if a dose-response type relationship exists.

3.2.1 Variables

Dependent Variables:

The dependent variables for this research are the measures of fitness achievement. The literature review supports that criteria air pollutants may be projected to have impacts on two of the six fitness measures evaluated within the state of California: Aerobic Capacity and Body Composition. No evidence was found to link exposure to criteria air pollutants with the remaining four measures of fitness: Abdominal Strength and Endurance, Trunk Extensor Strength, Upper Body Strength and Endurance and Flexibility. Therefore, as shown in Table 3.1, this analysis will focus only on Aerobic Capacity and Body Composition.

Table 3.1 Dependent Variables

Variable	Description	Variable Type	Allowable Values
AerCap	Reflects the percentage of children that met the criteria for acceptable aerobic capacity	Ratio	Values should range between 0 and 100%
BodFat	Reflects the percentage of children that had body fat measurements at an appropriate level	Ratio	Values should range between 0 and 100%

<u>Independent Variables:</u>

Three categories of independent variables were identified for this analysis: 1) Attainment Status variables, 2) Demographic variables, and 3) Other Environmental variables. These are discussed in further detail below.

Attainment Status:

The following variables (Table 3.2) were developed for each county within California. Counties were coded as to whether or not they were in attainment with a given NAAQS for either carbon monoxide, 8-hour Ozone, PM_{10} or $PM_{2.5}$.

Table 3.2 Independent Variables for Attainment Status

Variable	Description	Variable Type	Allowable Values
COATT	Carbon monoxide attainment status	Ordinal	0 = Attainment 1 = NonAttainment
O3ATT	8-hour Ozone attainment status	Ordinal	0 = Attainment 1 = NonAttainment
PM10ATT	PM10 Attainment status	Ordinal	0 = Attainment 1 = NonAttainment
PM2.5ATT	PM2.5 Attainment Status	Ordinal	0 = Attainment 1 = NonAttainment

These data were then linked to each school based on the county the school was located in for further analysis.

Demographic Variables:

Demographic variables (Table 3.3) are those "non-pollution" based variables that were anticipated to impact measures of physical fitness. These variables were available on a school-specific basis and were linked to the physical fitness data via the California school code. Data on Grade, Gender, and Ethnicity were on a class and school specific basis, whereas data on SES was available at the school level and was assumed to pertain to all classes within that school.

Table 3.3 Demographic Variables

Variable	**Description**	**Variable Type**	**Allowable Values**
Grade	Grade of students being evaluated (used as a surrogate for age)	Ordinal	5 = 5th grade 7 = 7th grade 9 = 9th grade
Gender	Gender of students being evaluated	Ordinal	2 = Female 3 = Male
PctMale	Percentage of male students by grade/school	Ratio	Values should range between 0 and 100%
BodFat	Reflects the percentage of children that had body fat measurements at an appropriate level	Ratio	Values should range between 0 and 100%
Ethnicity	Ethnicity of students being evaluated	Ordinal	Values range from 5-23 and represent the ethnicities specified by CDE (2009a)
PctMinority	Percentage of minority students by grade/school	Ratio	Values should range between 0 and 100%
SESQuartile	A categorized measure of students in a school receiving free or reduced price meals	Ordinal	1 – 1st Quartile 2 – 2nd Quartile 3 – 3rd Quartile 4 – 4th Quartile
PctSES	The percentage of students in a school receiving free or reduced price meals	Ratio	Values should range between 0 and 100%

Other Environmental Variables:

The following variables (Table 3.4) represent those variables used to assess Specific Aim #4. These variables include the number of days a criteria air pollutant exceeded its corresponding standard during the year preceding the fitness testing, the number of person days in the year preceding fitness testing, and the annual average concentrations in the year preceding testing. In addition, a variable for Air Quality Index (AQI) was created based on days that the AQI exceeded a value of 100 in the year preceding fitness testing.

Table 3.4 Other Environmental Variables

Variable	Description	Variable Type	Allowable Values
PreAQI	The number of days that the Air Quality Index in a county exceeded a value of 100 during the year preceding fitness testing	Ratio	Values should range between 0 and 365 days
PreO3Exceed	The number of days that the concentration of 8-hour Ozone in a county exceeded the NAAQS of 0.075ppm during the year preceding fitness testing	Ratio	Values should range between 0 and 365 days
PreO3PersonDays	The number of persons living in an exposed region times the number of days that 8-hour Ozone exceeded the National health standard in the year preceding fitness testing.	Ratio	Values should range between 0 and no upper limit
PreO3AnnAvg	The annual average concentration of 8-hour Ozone (in ppm) for May-Oct in the year preceding fitness testing	Ratio	Values should be 0 or higher
PrePM10Exceed	The number of days that the concentration of PM10 in a county exceeded the State standard of 50 ug/m^3 during the year preceding fitness testing	Ratio	Values should range between 0 and 365 days
PrePM10PersonDays	The number of persons living in an exposed region times the number of days that PM_{10} exceeded the State health standard in the year preceding fitness testing.	Ratio	Values should range between 0 and no upper limit
PrePM10AnnAvg	The annual average concentration of PM_{10} in ug/m^3 in the year preceding fitness testing	Ratio	Values should be 0 or higher

3.2.2 Specific Aim 1

The first set of hypotheses states that schools located in counties that are in non-attainment for CO, O_3, PM_{10}, or $PM_{2.5}$ will have lower overall passing rates for both aerobic capacity and body composition testing. In order to assess this hypothesis, a series of eight t-tests will be performed as shown in Table 3.5. Alpha will be set at 0.05.

Table 3.5 Statistical Tests to Evaluate Specific Aim 1

Test #	Dependent Variable (DV)	Independent Variable (IV)	Purpose
1	Aerobic Capacity (AerCap)	COATT	To determine if the DV differs by attainment status of the IV
2		O3ATT	
3		PM10ATT	
4		PM2.5ATT	
5	Body Composition (BodFat)	COATT	
6		O3ATT	
7		PM10ATT	
8		PM2.5ATT	

3.2.3 Specific Aim 2

The second set of hypotheses states that overall passing rates of aerobic capacity or body composition testing will differ by demographic variables (grade, gender, ethnicity, SES). This will be assessed through a combination of t-tests and one-way ANOVA analyses as shown in Table 3.6. Alpha will be set at 0.05.

Table 3.6 Statistical Tests to Evaluate Specific Aim 2

Test #	Test Type	Dependent Variable (DV)	Independent Variable (IV)	Purpose
1	T-test	Aerobic Capacity (AerCap)	Gender	To determine if the DV differs by demographic variable
2	1-way ANOVA		Grade	
3	1-way ANOVA		SESQuartile	
4	1-way ANOVA		Ethnicity	
5	T-test	Body Composition (BodFat)	COATT	
6	1-way ANOVA		O3ATT	
7	1-way ANOVA		PM10ATT	
8	1-way ANOVA		PM2.5ATT	

3.2.4 Specific Aim 3

The association of fitness achievement with criteria air pollutants requires more than just observing corresponding fluctuations between the two variables; it requires consideration and control of related factors. As such, the third set of hypotheses states that schools located in counties that are in non-attainment for CO, O_3, PM_{10}, or $PM_{2.5}$ will have lower overall passing rates for aerobic capacity testing after adjusting for key demographic variables. Related factors that were controlled for in this analysis include measures of Gender, Ethnicity, Socio-economic Status, and Age. The relationship between the dependent variable and the independent variables will be assessed using multiple regression, as shown in Table 3.7. Each regression model was controlled for a series of control variables which may influence the fitness outcome.

The purpose of these analyses is to describe the extent, direction and strength of the relationship between the air pollutant and the fitness measure being evaluated after controlling for demographic variables. Therefore, for each combination of the dependent variables (AerCap and BodFat) and criteria air pollutant (CO, O_3, PM_{10}, and $PM_{2.5}$), three different regression models were developed. The first model looked at the association between the dependent variable and a particular criteria air pollutant. The second model looked at the association between the dependent variable and the various demographic variables. The third model assessed the association between the dependent variable and a specific criteria air pollutant after adjusting for the demographic variables.

A correlation matrix was generated to examine the relationship between the independent and dependent variables and between the control variables. The Pearson Correlation value was examined to assess possible multicollinearity between the independent variables. The assumption for regression was no multicollinearity, which occurs when the independent variables are too highly correlated. In addition, tests for Tolerance and Variance Inflation Factor as measures of multicollinearity were conducted to ensure appropriate selection of the additional factors.

Table 3.7 Statistical Tests to Evaluate Specific Aim 3

Fitness Endpoint	Pollutant	Test #	Dependent Variable (DV)	Independent Variable (IV)	Purpose
Aerobic Capacity	Carbon Monoxide	1	AerCap	COATT	To describe the extent, direction and strength of the relationship between aerobic capacity and the air pollutant being evaluated after controlling for demographic variables
		2	AerCap	Demographic*	
		3	AerCap	Demographic + COATT	
	8-hour Ozone	4	AerCap	O3ATT	
		5	AerCap	Demographic	
		6	AerCap	Demographic + O3ATT	
	PM_{10}	7	AerCap	PM10ATT	
		8	AerCap	Demographic	
		9	AerCap	Demographic + PM10ATT	
	$PM_{2.5}$	10	AerCap	PM2.5ATT	
		11	AerCap	Demographic	
		12	AerCap	Demographic + PM2.5ATT	
Body Composition	Carbon Monoxide	13	BodFat	COATT	To describe the extent, direction and strength of the relationship between body composition and the air pollutant being evaluated after controlling for demographic variables
		14	BodFat	Demographic**	
		15	BodFat	Demographic + COATT	
	8-hour Ozone	16	BodFat	O3ATT	
		17	BodFat	Demographic	
		18	BodFat	Demographic + O3ATT	
	PM_{10}	19	BodFat	PM10ATT	
		20	BodFat	Demographic	
		21	BodFat	Demographic + PM10ATT	
	$PM_{2.5}$	22	BodFat	PM2.5ATT	
		23	BodFat	Demographic	
		24	BodFat	Demographic + PM2.5ATT	

* Demographic Variables for Aerobic Capacity = Grade, BodFat, PctMale, PctSES, and PctMinority

* * Demographic Variables for Body Fat = Grade, PctMale, PctSES, and PctMinority

The F-test was utilized to determine if at least one of the regression coefficients is significant ($p<0.05$). A t-test is conducted for each regression coefficient to determine if it is significant. The regression coefficients were determined and the correlation coefficient and amount of variance explained by the model were calculated.

3.2.5 Specific Aim 4

The fourth set of hypotheses relates to those criteria pollutants for which an association with aerobic capacity exists after adjustment for demographic factors. The goal is to determine if there is a dose response type relationship within those counties designated as non-attainment for a given pollutant. These variables were developed, because a county with a limited number of exceedances above its relevant standard leading to nonattainment status may have different health impacts than a county that has multiple exceedances of the air standard. In addition, counties with lower numbers of person days, or lower annual average concentrations may also have differing health impacts.

This Specific Aim was evaluated using multiple regression techniques similar to those for Specific Aim 3; however, the environmental variables were modified from attainment status to a measure of how many days per year within non-attainment areas the pollutant exceeds an allowable level. In addition, the annual mean concentration of the pollutant within the non-attainment counties was evaluated. The hypothesis states that as the number of air quality exceedances or average concentration for a given pollutant increases, the overall passing rate of schools for aerobic capacity testing will decrease.

The specific tests run for this analysis were dependent on the findings in the previous analysis, as only those criteria pollutants that were significant after adjusting for demographic factors were assessed. The focus was limited to aerobic capacity because the dependent variables were focused on the year preceding fitness testing, and body composition would not be expected to respond in as acute a timeframe as aerobic capacity. As seen in Section 4, only carbon monoxide, 8-hour ozone, and PM10 were significant after adjusting for demographic factors.

However, carbon monoxide had insufficient data available for further testing. Only four counties in California were designated as non-attainment status in 2006. No counties were classified as non-attainment in 2006. According to the California Air Resources Board (2009), the Salton Air Basin only had one day exceeding the national standard for carbon monoxide during 2006. Thus, data were not sufficient to develop variables and perform further regression analyses. Therefore, the following multiple regression analyses were conducted for 8-hour ozone and PM_{10}, in order to determine if there was a dose-response type response for these pollutants when looking at only those counties designated as non-attainment.

Table 3.8 Statistical Tests to Evaluate Specific Aim 4

Environmental Endpoint	Pollutant	Test #	Dependent Variable (DV)	Independent Variable (IV)
# of Exceedances	8-hour Ozone	1	AerCap	PreO3Exceed
		2	AerCap	Demographic*
		3	AerCap	Demographic + PreO3Exceed
	PM_{10}	4	AerCap	PrePM10Exceed
		5	AerCap	Demographic
		6	AerCap	Demographic + PrePM10Exceed
# of Person Days	8-hour Ozone	7	AerCap	PreO3PersDays
		8	AerCap	Demographic
		9	AerCap	Demographic + PreO3PersDays
	PM_{10}	10	AerCap	PrePM10PersDays
		11	AerCap	Demographic
		12	AerCap	Demographic + PrePM10PersDays
Annual Average Concentration	8-hour Ozone	13	AerCap	PreO3AnnAvg
		14	AerCap	Demographic
		15	AerCap	Demographic + PreO3AnnAvg
	PM_{10}	16	AerCap	PrePM10AnnAvg
		17	AerCap	Demographic
		18	AerCap	Demographic + PrePM10AnnAvg
Air Quality Index	AQI	19	AerCap	PreAQI
		20	AerCap	Demographic
		21	AerCap	Demographic + PreAQI

* Demographic Variables = Grade, BodFat, PctMale, and PctSES

3.3 Chapter Summary

This chapter provided a detailed description of the methodology to be used in evaluating whether or not a relationship exists between ambient air pollutants, specifically carbon monoxide, 8-hour ozone, PM_{10} and $PM_{2.5}$, and aerobic capacity passing rates and body composition passing rates for children tested under the California physical fitness testing program. This chapter provided detailed descriptions of the independent and dependent variables to be used in the analyses. A tiered approach was proposed to assess the association of the four criteria air pollutants with the physical fitness outcomes. The study was divided into four different specific aims for which statistical methods were identified.

CHAPTER IV

FINDINGS

The purpose of this study was to determine if a relationship exists between ambient air pollutants, specifically carbon monoxide, 8-hour ozone, PM_{10} and $PM_{2.5}$, and aerobic capacity and body composition passing rates in children tested under the California physical fitness testing program during 2006 and 2007. Therefore a series of statistical analyses were identified and performed. Under Specific Aim 1, a series of t-tests were conducted to determine if physical fitness differs between attainment and non-attainment areas. For Specific Aim 2, both t-tests and one-way ANOVA's were used to identify explanatory variables. Multivariate regression models were constructed to evaluate the strength of the association between fitness achievement and attainment status (Specific Aim 3) or quantitative environmental metrics (Specific Aim 4) after controlling for demographic variables such as gender, SES, grade, and ethnicity.

This study was conducted using California physical fitness testing data from 2006 and 2007 for 5th, 7th, and 9th graders and resulted in an overall dataset consisting of fitness testing for over 2.7 million children aggregated into 17,293 grade/school combinations. This study focused on carbon monoxide, 8-hour ozone, PM10 and PM2.5, as these were non-attainment pollutants in various California counties during the study timeframe. A summary of attainment status by criteria air pollutant for each county is provided in Appendix B of this report. In 2006, four California counties were designated as non-attainment for carbon monoxide. By 2007, no counties remained designated with this status. Despite the relatively small number of counties designated as non-attainment for carbon monoxide during the study timeframe, these counties contained a large number of public schools. A total of 3,301 (19%) grade/school records were located in non-attainment areas for this study, versus 13,992 (81%) grade/school records in areas classified as attainment. For 8-hour ozone, thirty-five of the 58 California counties were designated as non-attainment areas during 2006 and 2007. Although only 60.3% of the 58 counties in California were designated as non-attainment areas, due to the distribution of schools within the non-attainment areas, this resulted in 90.8% (n=15,704) of the data records being classified in this study as non-attainment and 9.2% (n=1,589) being classified as attainment. Because this exceeded an acceptable 90/10 split, the data were split into attainment areas (n=1,589) versus severe non-attainment areas (n=2,904) as designated in the USEPA Greenbook (USEPA, 2009b). This reduced data set was utilized for the grouped statistical analyses (i.e., t-test), and the full data set was utilized for the ungrouped analyses (i.e., multiple regression). During both 2006 and 2007, fifteen of the 58 counties and twelve of the 58 counties in California were designated as non-attainment areas for PM_{10} and $PM_{2.5}$, respectively. These non-attainment areas represented 57.4% of the physical fitness records for PM_{10} and 53.2% of the records for $PM_{2.5}$ in this study.

Of the 17,293 data records used for the analysis, 10,527 (60.9%) of the records contained aggregate fitness testing results for 5th graders at an individual school, 4,037 (23.3%) were for 7th graders, and 2,729 (15.8%) were for 9th graders. This observed decrease in the number of records as grade levels increase is expected, as communities tend to have more elementary schools (5th grade) than middle schools (7th grade) or high schools (9th grade).

For the evaluation of aerobic capacity and body composition passing rates by gender, a new dataset was created that contained separate fitness results for males and females. This in essence doubled the base dataset for this analysis, resulting in a total of 32,455 records, of which 49.6% were physical fitness testing results for females within a grade at a school, and 50.4% were results for males within a grade at a school. This dataset was used solely for the purposes of assessing if gender was associated with physical fitness outcomes via t-tests under Specific Aim 2. For multiple regression analyses, this gender specific dataset was used to create a variable on the percentage of males in each grade at an individual school. This new variable (PctMale) was then cross linked to the original dataset of 17,293 records for use in multiple regression analyses.

As for gender, the evaluation of aerobic capacity and body composition passing rates by ethnicity required the development of a separate dataset containing fitness results by ethnicity. This dataset consisted of a total of 37,370 records containing physical fitness testing results for various ethnicities within a grade at a school. The total count of records by ethnicity is provided in Table 4.16. This dataset was used solely for the purposes of assessing if ethnicity was associated with physical fitness outcomes via ANOVA under Specific Aim 2. For multiple regression analyses, this ethnicity specific dataset was used to create a variable on the percentage of minorities (non-White) in each grade at an individual school. This new variable (PctMinority) was then cross linked to the original dataset of 17,293 records for use in multiple regression analyses.

The analyses in this report focused on four criteria air pollutants, carbon monoxide, 8-hour ozone, PM_{10} and $PM_{2.5}$, because areas of California were determined to be in non-attainment for these four pollutants during the 2006 and 2007 study timeframe. In addition, the study focused on only two of the six measures of physical fitness assessed in the California physical fitness testing program. These fitness endpoints were aerobic capacity and body composition passing rates, and were identified based on a review of the scientific literature in Chapter 2 of this report that suggested a possible association between exposure to criteria air pollutants and decrements in these fitness endpoints.

The following sections summarize the results of the statistical analyses that were performed in accord with the methodology specified in Chapter 3 of this document.

4.1 Specific Aim 1

To examine the association between attainment status for CO, O_3, PM_{10}, and $PM_{2.5}$ and measures of aerobic capacity or body composition in children.

4.1.1 Aerobic Capacity

4.1.1.1 Carbon Monoxide

Prior to the analysis, the independent variable Carbon Monoxide Attainment Status (COATT) and the dependent variable Aerobic Capacity (AerCap) were screened for accuracy and the assumptions of a t-test. First, the data were screened for missing values. Both Carbon Monoxide Attainment Status and Aerobic Capacity were determined to have no missing data.

Next, the data were screened for univariate outliers using descriptive statistics, stem and leaf plots, and boxplots. All values of Carbon Monoxide Attainment Status were within range, so no data were out of range. Carbon Monoxide Attainment Status was within the requirements of the below than 90%/10% split. Therefore, it did not have univariate outliers. Because the analysis involved grouped data, Aerobic Capacity was split by attainment status so that each group could be assessed. Values for each group were within range and the means and standard deviations appeared plausible. Stem and leaf plots and boxplots for both the Attainment and Non-Attainment subgroups indicated no outliers. No outlier treatment was necessary.

Then, data were screened for univariate normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms indicated a slight negative skew for both attainment and non-attainment groups, but distributions were unimodal. The Q-Q plots each showed little skew for attainment and non-attainment.

Descriptive statistics were generated next for each group. The skewness of -0.522 for Attainment areas and -0.425 for Non-Attainment areas were both within the benchmark levels of $\pm$1.0. The kurtosis of -0.324 for Attainment areas and -0.365 for Non-Attainment areas were within the kurtosis benchmark of ±2.0. Thus, the assumption of a normal distribution was satisfied and no further transformations were required.

The final assumption for a t-test is homogeneity of variance, which was assessed with boxplots and Levene's Test for Equality of Variances. The non-attainment box portion of the plot was slightly taller than the attainment box, indicating more variation. The more precise Levene's Test resulted in a p-value of 0.449, indicating the variances were equal. Thus, all assumptions of a t-test have been satisfied.

The hypothesis predicted that Aerobic Capacity would be higher in Carbon Monoxide Attainment areas than in Carbon Monoxide Non-Attainment areas. Descriptive statistics were generated. The mean Aerobic Capacity for Carbon Monoxide Attainment areas was 59.57 and was absolutely larger than the mean value for Non-Attainment Areas of 56.76.

A t-test was used to determine whether the two means were statistically different. Because the hypothesis predicted that schools in attainment areas would have higher overall passing rates, a one-tailed test was used. Alpha was set at 0.05, but it is assessed as 0.10 in SPSS because it only reports the values of two-tailed tests.

Table 4.1
T-test Comparing Aerobic Capacity by Carbon Monoxide Attainment Status

Level	N	Mean	S.D.	T	Eta	Eta-Squared
Attainment	13992	59.57	22.60	6.436**	0.049	0.002
Non-Attainment	3301	56.76	22.44			

***p <0.05 ** p<0.01**

As Table 4.1 shows ($t(d.f. = 17291)=6.436$, $p <0.001$), schools located within attainment areas ($M=59.57$) were statistically more likely to have a higher percentage of students passing Aerobic Capacity fitness testing than were schools in Non-Attainment areas ($M=56.76$). Thus, this hypothesis was supported. An analysis of association using eta ($\eta=0.049$) indicated a very weak positive relationship between Carbon Monoxide attainment status and Aerobic Capacity, according to Frankfort-Nachmias and Leon-Guerrero's guidelines (Frankfort-Nachmias and Leon-Guerrero, 2002). Eta squared was used to determine the effect size ($\eta^2 = 0.002$). Carbon Monoxide attainment status explained 0.2% of the variation in Aerobic Capacity.

4.1.1.2 8-hour Ozone

Prior to the analysis, the independent variable Ozone Attainment Status (O3ATT) and the dependent variable Aerobic Capacity (AerCap) were screened for accuracy and the assumptions of a t-test. First, the data were screened for missing values. Both Ozone Attainment Status and Aerobic Capacity were determined to have no missing data.

Next, the data were screened for univariate outliers using descriptive statistics, stem and leaf plots, and boxplots. All values of Ozone Attainment Status were within range, so no data were out of range. Ozone Attainment Status was slightly outside of the requirements of the below than 90%/10% split. Therefore, the data were split to focus on the difference between ozone attainment areas and areas that were classified by the USEPA as severe, whole county ozone non-attainment areas (USEPA, 2009b). The resulting data split was 35.4% attainment and 64.6% severe non-attainment. This is within the desired range of below 90/10. Because the analysis involved grouped data, Aerobic Capacity was split by attainment status so that each group could be assessed. Values for each group were within range and the means and standard deviations appeared plausible. Stem and leaf plots and boxplots indicated the presence of several possible outliers for Ozone Attainment within Aerobic Capacity. Despite this fact, the z-scores for Ozone Attainment were found to be within the allowable standard of ± 3.0. Therefore, the datapoints in question were retained in the dataset with no treatment required. Stem and leaf plots and boxplots for the Severe Non-Attainment subgroup indicated no outliers. No outlier treatment was necessary.

Then, data were screened for univariate normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms indicated a slight negative skew for both attainment and severe non-attainment groups, but distributions were unimodal. The Q-Q plots each showed little skew for attainment and non-attainment.

Descriptive statistics were generated next for each group. The skewness of -0.558 for Attainment areas and -0.380 for Severe Non-Attainment areas were both within the benchmark levels of $\pm$1.0. The kurtosis of -0.093 for Attainment areas and -0.437 for Severe Non-Attainment areas were within the kurtosis benchmark of $\pm$2.0. Thus, the assumption of a normal distribution was satisfied and no further transformations were required.

The final assumption for a t-test is homogeneity of variance, which was assessed with boxplots and Levene's Test for Equality of Variances. The severe non-attainment box portion appeared similar to the attainment box, indicating equal variation. The more precise Levene's Test resulted in a p-value of 0.027, indicating the variances were not equal. Thus, the assumption of homogeneity of variance was not satisfied and the alternate t-test for equal variances not assumed was utilized.

The hypothesis predicted that Aerobic Capacity would be higher in Ozone Attainment areas than in Ozone Severe Non-Attainment areas. Descriptive statistics were generated. The mean Aerobic Capacity for Ozone Attainment areas was 60.85 and was absolutely larger than the mean value for Severe Non-Attainment Areas of 55.92.

A t-test was used to determine whether the two means were statistically different. Because the hypothesis predicted that schools in attainment areas would have higher overall passing rates, a one-tailed test was used. Alpha was set at 0.05, but it is assessed as 0.10 in SPSS because it only reports the values of two-tailed tests.

Table 4.2
T-test Comparing Aerobic Capacity by 8-Hour Ozone Attainment Status

Level	N	Mean	S.D.	T	Eta	Eta-Squared
Attainment	**1589**	**60.85**	**21.49**	**7.259****	**0.107**	**0.011**
Severe Non-Attainment	**2904**	**55.92**	**22.23**			

***p <0.05 ** p<0.01**

As Table 4.2 shows (t(d.f. = 3361)=7.259, $p < 0.001$), schools located within attainment areas (M=60.85) were statistically more likely to have a higher percentage of students passing Aerobic Capacity fitness testing than were schools in Severe Non-Attainment areas (M=55.92). Thus, this hypothesis was supported. An analysis of association using eta (η=0.107) indicated a very weak positive relationship between Ozone attainment status and Aerobic Capacity, according to Frankfort-Nachmias and Leon-Guerrero's guidelines (Frankfort-Nachmias and Leon-Guerrero, 2002). Eta squared was used to determine the effect size ($\eta^2 = 0.011$). Ozone attainment status explained 1.1% of the variation in Aerobic Capacity.

4.1.1.3 PM_{10}

Prior to the analysis, the independent variable PM_{10} Attainment Status (PM10ATT) and the dependent variable Aerobic Capacity (AerCap) were screened for accuracy and the assumptions of a t-test. First, the data were screened for missing values. Both PM_{10} Attainment Status and Aerobic Capacity were determined to have no missing data.

Next, the data were screened for univariate outliers using descriptive statistics, stem and leaf plots, and boxplots. All values of PM_{10} Attainment Status were within range, so no data were out of range. PM_{10} Attainment Status was within the requirements of the below than 90%/10% split. Therefore, it did not have univariate outliers. Because the analysis involved grouped data, Aerobic Capacity was split by attainment status so that each group could be assessed. Values for each group were within range and the means and standard deviations appeared plausible. Stem and leaf plots and boxplots for both the Attainment and Non-Attainment subgroups indicated no outliers. No outlier treatment was necessary.

Then, data were screened for univariate normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms indicated a slight negative skew for both attainment and non-attainment groups, but distributions were unimodal. The Q-Q plots each showed little skew for attainment and non-attainment.

Descriptive statistics were generated next for each group. The skewness of -0.635 for Attainment areas and -0.416 for Non-Attainment areas were both within the benchmark levels of $\pm$1.0. The kurtosis of -0.185 for Attainment areas and -0.390 for Non-Attainment areas were within the kurtosis benchmark of $\pm$2.0. Thus, the assumption of a normal distribution was satisfied and no further transformations were required.

The final assumption for a t-test is homogeneity of variance, which was assessed with boxplots and Levene's Test for Equality of Variances. The non-attainment box portion of the plot was slightly taller than the attainment box, indicating more variation. The more precise Levene's Test resulted in a p-value of 0.849, indicating the variances were equal. Thus, all assumptions of a t-test have been satisfied.

The hypothesis predicted that Aerobic Capacity would be higher in PM_{10} Attainment areas than in PM_{10} Non-Attainment areas. Descriptive statistics were generated. The mean Aerobic Capacity for PM_{10} Attainment areas was 61.55 and was absolutely larger than the mean value for Non-Attainment Areas of 57.16.

A t-test was used to determine whether the two means were statistically different. Because the hypothesis predicted that schools in attainment areas would have higher overall passing rates, a one-tailed test was used. Alpha was set at 0.05, but it is assessed as 0.10 in SPSS because it only reports the values of two-tailed tests.

Table 4.3
T-test Comparing Aerobic Capacity by PM_{10} Attainment Status

Level	N	Mean	S.D.	T	Eta	Eta-Squared
Attainment	**7373**	**61.55**	**22.61**	**12.685****	**0.096**	**0.009**
Non-Attainment	**9920**	**57.16**	**22.40**			

***p <0.05 ** p<0.01**

As Table 4.3 shows (t(d.f. = 17285)=12.646, p <0.001), schools located within attainment areas (M=61.55) were statistically more likely to have a higher percentage of students passing Aerobic Capacity fitness testing than were schools in Non-Attainment areas (M=57.16). Thus, this hypothesis was supported. An analysis of association using eta (η=0.096) indicated a very weak positive relationship between PM_{10} attainment status and Aerobic Capacity, according to Frankfort-Nachmias and Leon-Guerrero's guidelines (Frankfort-Nachmias and Leon-Guerrero, 2002). Eta squared was used to determine the effect size (η^2 = 0.009). PM_{10} attainment status explained 0.9% of the variation in Aerobic Capacity.

4.1.1.4 $PM_{2.5}$

Prior to the analysis, the independent variable $PM_{2.5}$ Attainment Status (PM2.5ATT) and the dependent variable Aerobic Capacity (AerCap) were screened for accuracy and the assumptions of a t-test. First, the data were screened for missing values. Both $PM_{2.5}$ Attainment Status and Aerobic Capacity were determined to have no missing data.

Next, the data were screened for univariate outliers using descriptive statistics, stem and leaf plots, and boxplots. All values of $PM_{2.5}$ Attainment Status were within range, so no data were out of range. $PM_{2.5}$ Attainment Status was within the requirements of the below than 90%/10% split. Therefore, it did not have univariate outliers. Because the analysis involved grouped data, Aerobic Capacity was split by attainment status so that each group could be assessed. Values for each group were within range and the means and standard deviations appeared plausible. Stem and leaf plots and boxplots for both the Attainment and Non-Attainment subgroups indicated no outliers. No outlier treatment was necessary.

Then, data were screened for univariate normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms indicated a slight negative skew for both attainment and non-attainment groups, but distributions were unimodal. The Q-Q plots each showed little skew for attainment and non-attainment.

Descriptive statistics were generated next for each group. The skewness of -0.614 for Attainment areas and -0.414 for Non-Attainment areas were both within the benchmark levels of $\pm$1.0. The kurtosis of -0.226 for Attainment areas and -0.381 for Non-Attainment areas were within the kurtosis benchmark of $\pm$2.0. Thus, the assumption of a normal distribution was satisfied and no further transformations were required.

The final assumption for a t-test is homogeneity of variance, which was assessed with boxplots and Levene's Test for Equality of Variances. The non-attainment box portion of the plot was slightly taller than the attainment box, indicating more variation. The more precise Levene's Test resulted in a p-value of 0.805, indicating the variances were equal. Thus, all assumptions of a t-test have been satisfied.

The hypothesis predicted that Aerobic Capacity would be higher in $PM_{2.5}$ Attainment areas than in $PM_{2.5}$ Non-Attainment areas. Descriptive statistics were generated. The mean Aerobic Capacity for $PM_{2.5}$ Attainment areas was 61.09 and was absolutely larger than the mean value for Non-Attainment Areas of 57.22.

A t-test was used to determine whether the two means were statistically different. Because the hypothesis predicted that schools in attainment areas would have higher overall passing rates, a one-tailed test was used. Alpha was set at 0.05, but it is assessed as 0.10 in SPSS because it only reports the values of two-tailed tests.

As Table 4.4 shows (t(d.f. = 17291)=11.29, p <0.001), schools located within attainment areas (M=61.09) were statistically more likely to have a higher percentage of students passing Aerobic Capacity fitness testing than were schools in Non-Attainment areas (M=57.22). Thus, this hypothesis was supported. An analysis of association using eta (η=0.086) indicated a very weak positive relationship between $PM_{2.5}$ attainment status and Aerobic Capacity, according to Frankfort-Nachmias and Leon-Guerrero's guidelines (Frankfort-Nachmias and Leon-Guerrero, 2002). Eta squared was used to determine the effect size ($\eta^2 = 0.007$). $PM_{2.5}$ attainment status explained 0.7% of the variation in Aerobic Capacity.

Table 4.4
T-test Comparing Aerobic Capacity by $PM_{2.5}$ Attainment Status

Level	N	Mean	S.D.	T	Eta	Eta-Squared
Attainment	**8095**	**61.09**	**22.60**	**11.29****	**0.086**	**0.007**
Non-Attainment	**9198**	**57.22**	**22.44**			

***p <0.05 ** p<0.01**

4.1.2 Body Composition

4.1.2.1 Carbon Monoxide

Prior to the analysis, the independent variable Carbon Monoxide Attainment Status (COATT) and the dependent variable Body Fat (BodFat) were screened for accuracy and the assumptions of a t-test. First, the data were screened for missing values. Both Carbon Monoxide Attainment Status and Body Fat were determined to have no missing data.

Next, the data were screened for univariate outliers using descriptive statistics, stem and leaf plots, and boxplots. All values of Carbon Monoxide Attainment Status were within range, so no data were out of range. Carbon Monoxide Attainment Status was within the requirements of the below than 90%/10% split. Therefore, it did not have univariate outliers. Because the analysis involved grouped data, Body Fat was split by attainment status so that each group could be assessed. Values for each group were within range and the means and standard deviations appeared plausible. The stem and leaf plots and the boxplots for both Attainment and NonAttainment within Body Fat indicated multiple outliers at the lower end of the distribution. In addition, several outliers were indicated on the upper end of the distribution for NonAttainment. The z-scores for the Attainment and NonAttainment subgroups supported the finding of potential outliers within the dataset as several z-scores were outside the allowable $\pm$3.0. The datasets were treated by performing two repetitions of Windsorization which resulted in values for Body Fat in the Attainment data set which were less than 30.4% being replaced with values of 31.4%. Values for Body Fat in the NonAttainment data set which were less than 32.6% were replaced with values of 33.6%.

Then, data were screened for univariate normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms indicated a unimodal, normal distributions for both attainment and non-attainment groups. The Q-Q plots each showed little skew for attainment and non-attainment.

Descriptive statistics were generated next for each group. The skewness of -0.324 for Attainment areas and -0.105 for Non-Attainment areas were both within the benchmark levels of $\pm$1.0. The kurtosis of 0.378 for Attainment areas and 0.145 for Non-Attainment areas were within the kurtosis benchmark of $\pm$2.0. Thus, the assumption of a normal distribution was satisfied and no further transformations were required.

The final assumption for a t-test is homogeneity of variance, which was assessed with boxplots and Levene's Test for Equality of Variances. The non-attainment and attainment boxes on the plot appeared similar, indicating equal variation. The more precise Levene's Test resulted in a p-value of 0.001, indicating the variances were not equal. Thus, the assumption of homogeneity of variance was not satisfied and the alternate t-test for equal variances not assumed was utilized.

The hypothesis predicted that Body Fat would be higher in Carbon Monoxide Attainment areas than in Carbon Monoxide Non-Attainment areas. Descriptive statistics were generated. The mean Body Fat for Carbon Monoxide Attainment areas was 68.04 and was absolutely larger than the mean value for Non-Attainment Areas of 66.40.

A t-test was used to determine whether the two means were statistically different. Because the hypothesis predicted that schools in attainment areas would have higher overall passing rates, a one-tailed test was used. Alpha was set at 0.05, but it is assessed as 0.10 in SPSS because it only reports the values of two-tailed tests.

Table 4.5
T-test Comparing Body Fat by Carbon Monoxide Attainment Status

Level	N	Mean	S.D.	T	Eta	Eta-Squared
Attainment	13992	68.04	12.43	7.154**	0.052	0.003
Non-Attainment	3301	66.40	11.74			

*p <0.05 ** p<0.01

As Table 4.5 shows (t(d.f. = 5193)=7.154, p <0.001), schools located within attainment areas (M=68.04) were statistically more likely to have a higher percentage of students passing Body Fat fitness testing than were schools in Non-Attainment areas (M=66.40). Thus, this hypothesis was supported. An analysis of association using eta (η=0.052) indicated a very weak positive relationship between Carbon Monoxide attainment status and Body Fat, according to Frankfort-Nachmias and Leon-Guerrero's guidelines (Frankfort-Nachmias and Leon-Guerrero, 2002). Eta squared was used to determine the effect size ($\eta^2 = 0.003$). Carbon Monoxide attainment status explained 0.3% of the variation in Body Fat.

4.1.2.2 8-hour Ozone

Prior to the analysis, the independent variable Ozone Attainment Status (O3ATT) and the dependent variable Body Fat (BodFat) were screened for accuracy and the assumptions of a t-test. First, the data were screened for missing values. Both Ozone Attainment Status and Body Fat were determined to have no missing data.

Next, the data were screened for univariate outliers using descriptive statistics, stem and leaf plots, and boxplots. All values of Ozone Attainment Status were within range, so no data were out of range. Ozone Attainment Status was slightly outside of the requirements of the below than 90%/10% split. Therefore, the data were split to focus on the difference between ozone attainment areas and areas that were classified by the USEPA as severe, whole county ozone non-attainment areas (USEPA, 2009b). The resulting data split was 35.4% attainment and 64.6% severe non-attainment. This is within the desired range of below 90/10. Because the analysis involved grouped data, Body Fat was split by attainment status so that each group could be assessed. Values for each group were within range and the means and standard deviations appeared plausible.

Stem and leaf plots and boxplots indicated the presence of several possible outliers for Ozone Attainment within Body Fat. The z-scores for the Attainment subgroup supported the finding of outliers within the dataset as the z-score is outside the allowable ±3.0. The dataset was Winsorized twice to reduce the influence of the outliers by replacing all Body Fat passing rate values of less than 30.8% with a value of 31.8%. The stem and leaf plot and the boxplot indicated multiple outliers at the lower and upper ends of the distribution. The z-scores for several points within the Severe NonAttainment subgroup were outside the allowable ±3.0. The dataset was Winsorized twice to reduce the influence of the outliers by replacing all Body Fat passing rate values of less than 32% with a value of 33% and replacing all values higher than 99% with a value of 98%.

Then, data were screened for univariate normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms indicated unimodal, normal distributions for both attainment and severe non-attainment groups. The Q-Q plots each showed little skew for attainment and non-attainment.

Descriptive statistics were generated next for each group. The skewness of -0.360 for Attainment areas and -0.312 for Severe Non-Attainment areas were both within the benchmark levels of ±1.0. The kurtosis of 0.368 for Attainment areas and 0.693 for Severe Non-Attainment areas were within the kurtosis benchmark of ±2.0. Thus, the assumption of a normal distribution was satisfied and no further transformations were required.

The final assumption for a t-test is homogeneity of variance, which was assessed with boxplots and Levene's Test for Equality of Variances. The severe non-attainment box portion appeared similar to the attainment box, indicating equal variation. The more precise Levene's Test resulted in a p-value of <0.001, indicating the variances were not equal. Thus, the assumption of homogeneity of variance was not satisfied and the alternate t-test for equal variances not assumed was utilized.

The hypothesis predicted that Body Fat would be higher in Ozone Attainment areas than in Ozone Severe Non-Attainment areas. Descriptive statistics were generated. The mean Body Fat for Ozone Attainment areas was 68.40 and was absolutely larger than the mean value for Severe Non-Attainment Areas of 65.63.

A t-test was used to determine whether the two means were statistically different. Because the hypothesis predicted that schools in attainment areas would have higher overall passing rates, a one-tailed test was used. Alpha was set at 0.05, but it is assessed as 0.10 in SPSS because it only reports the values of two-tailed tests.

As Table 4.6 shows (t(d.f. = 2927)=7.346, p <0.001), schools located within attainment areas (M=68.40) were statistically more likely to have a higher percentage of students passing Body Fat fitness testing than were schools in Severe Non-Attainment areas (M=65.63). Thus, this hypothesis was supported. An analysis of association using eta (η=0.113) indicated a very weak positive relationship between Ozone attainment status and Body Fat, according to Frankfort-Nachmias and Leon-Guerrero's guidelines (Frankfort-Nachmias and Leon-Guerrero, 2002). Eta squared was used to determine the effect size (η^2 = 0.013). Ozone attainment status explained 1.3% of the variation in Body Fat.

Table 4.6
T-test Comparing Body Fat by 8-hour Ozone Attainment Status

Level	N	Mean	S.D.	T	Eta	Eta-Squared
Attainment	1589	68.40	12.62	7.346**	0.113	0.013
Severe Non-Attainment	2904	65.63	11.09			

***p <0.05 ** p<0.01**

4.1.2.3 PM_{10}

Prior to the analysis, the independent variable PM_{10} Attainment Status (PM10ATT) and the dependent variable Body Fat (BodFat) were screened for accuracy and the assumptions of a t-test. First, the data were screened for missing values. Both PM_{10} Attainment Status and Body Fat were determined to have no missing data.

Next, the data were screened for univariate outliers using descriptive statistics, stem and leaf plots, and boxplots. All values of PM_{10} Attainment Status were within range, so no data were out of range. PM_{10} Attainment Status was within the requirements of the below than 90%/10% split. Therefore, it did not have univariate outliers. Because the analysis involved grouped data, Body Fat was split by attainment status so that each group could be assessed. Values for each group were within range and the means and standard deviations appeared plausible. The stem and leaf plots and the boxplots for both Attainment and NonAttainment within Body Fat indicated multiple outliers at the lower end of the distribution. In addition, several outliers were indicated on the upper end of the distribution for NonAttainment. The z-scores for the Attainment and NonAttainment subgroups supported the finding of potential outliers within the dataset as several z-scores were outside the allowable ± 3.0. The datasets were treated by performing two repetitions of Windsorization which resulted in values for Body Fat in the Attainment data set which were less than 30.4% being replaced with values of 31.4%. Values for Body Fat in the NonAttainment data set which were less than 31% were replaced with values of 32%.

Then, data were screened for univariate normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms indicated a unimodal, normal distributions for both attainment and non-attainment groups. The Q-Q plots each showed little skew for attainment and non-attainment.

Descriptive statistics were generated next for each group. The skewness of -0.496 for Attainment areas and -0.177 for Non-Attainment areas were both within the benchmark levels of ± 1.0. The kurtosis of 0.456 for Attainment areas and 0.382 for Non-Attainment areas were within the kurtosis benchmark of $\pm$2.0. Thus, the assumption of a normal distribution was satisfied and no further transformations were required.

The final assumption for a t-test is homogeneity of variance, which was assessed with boxplots and Levene's Test for Equality of Variances. The Attainment box portion of the plot was slightly taller than the attainment box, indicating more variation. The more precise Levene's Test resulted in a p-value of <0.001, indicating the variances were not equal. Thus, the assumption of homogeneity of variance was not satisfied and the alternate t-test for equal variances not assumed was utilized.

The hypothesis predicted that Body Fat would be higher in PM_{10} Attainment areas than in PM_{10} Non-Attainment areas. Descriptive statistics were generated. The mean Body Fat for PM_{10} Attainment areas was 69.79 and was absolutely larger than the mean value for Non-Attainment Areas of 66.20.

A t-test was used to determine whether the two means were statistically different. Because the hypothesis predicted that schools in attainment areas would have higher overall passing rates, a one-tailed test was used. Alpha was set at 0.05, but it is assessed as 0.10 in SPSS because it only reports the values of two-tailed tests.

Table 4.7
T-test Comparing Body Fat by PM_{10} Attainment Status

Level	N	Mean	S.D.	T	Eta	Eta-Squared
Attainment	7373	69.79	12.98	18.834**	0.144	0.021
Non-Attainment	9920	66.20	11.57			

***p <0.05 ** p<0.01**

As Table 4.7 shows (t(d.f. = 14812)=18.834, $p < 0.001$), schools located within attainment areas (M=69.79) were statistically more likely to have a higher percentage of students passing Body Fat fitness testing than were schools in Non-Attainment areas (M=66.20). Thus, this hypothesis was supported. An analysis of association using eta (η=0.144) indicated a very weak positive relationship between PM_{10} attainment status and Body Fat, according to Frankfort-Nachmias and Leon-Guerrero's guidelines (Frankfort-Nachmias and Leon-Guerrero, 2002). Eta squared was used to determine the effect size ($\eta^2 = 0.021$). PM_{10} attainment status explained 2.1% of the variation in Body Fat.

4.1.2.4 $PM_{2.5}$

Prior to the analysis, the independent variable $PM_{2.5}$ Attainment Status (PM2.5ATT) and the dependent variable Body Fat (BodFat) were screened for accuracy and the assumptions of a t-test. First, the data were screened for missing values. Both $PM_{2.5}$ Attainment Status and Body Fat were determined to have no missing data.

Next, the data were screened for univariate outliers using descriptive statistics, stem and leaf plots, and boxplots. All values of $PM_{2.5}$ Attainment Status were within range, so no data were out of range. $PM_{2.5}$ Attainment Status was within the requirements of the below than 90%/10% split. Therefore, it did not have univariate outliers. Because the analysis involved grouped data, Body Fat was split by attainment status so that each group could be assessed. Values for each group were within range and the means and standard deviations appeared plausible. The stem and leaf plots and the boxplots for both Attainment and NonAttainment within Body Fat indicated multiple outliers at the lower end of the distribution. In addition, several outliers were indicated on the upper end of the distribution for NonAttainment. The z-scores for the Attainment and NonAttainment subgroups supported the finding of potential outliers within the dataset as several z-scores were outside the allowable ± 3.0. The datasets were treated by performing two repetitions of Windsorization which resulted in values for Body Fat in the Attainment data set that were less than 30.4% being replaced with values of 31.4%. Values for Body Fat in the NonAttainment data set which were less than 31.7% were replaced with values of 32.7%.

Then, data were screened for univariate normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms for both $PM_{2.5}$ Attainment and NonAttainment indicated unimodal datasets with a normal distribution for Attainment and a slight skew for NonAttainment. Additionally, the Q-Q Probability Plots for both $PM_{2.5}$ subsets indicated little skew.

Descriptive statistics were generated next for each group. The skewness of -0.516 for Attainment areas and -0.102 for Non-Attainment areas were both within the benchmark levels of $\pm$1.0. The kurtosis of 0.500 for Attainment areas and 0.308 for Non-Attainment areas were within the kurtosis benchmark of $\pm$2.0. Thus, the assumption of a normal distribution was satisfied and no further transformations were required.

The final assumption for a t-test is homogeneity of variance, which was assessed with boxplots and Levene's Test for Equality of Variances. The Attainment box portion of the plot was slightly taller than the attainment box, indicating more variation. The more precise Levene's Test resulted in a p-value of <0.001, indicating the variances were not equal. Thus, the assumption of homogeneity of variance was not satisfied and the alternate t-test for equal variances not assumed was utilized. This test compensates for the violation of the assumption.

The hypothesis predicted that Body Fat would be higher in $PM_{2.5}$ Attainment areas than in $PM_{2.5}$ Non-Attainment areas. Descriptive statistics were generated. The mean Body Fat for $PM_{2.5}$ Attainment areas was 69.62 and was absolutely larger than the mean value for Non-Attainment Areas of 66.07.

A t-test was used to determine whether the two means were statistically different. Because the hypothesis predicted that schools in attainment areas would have higher overall passing rates, a one-tailed test was used. Alpha was set at 0.05, but it is assessed as 0.10 in SPSS because it only reports the values of two-tailed tests.

Table 4.8
T-test Comparing Body Fat by $PM_{2.5}$ Attainment Status

Level	N	Mean	S.D.	T	Eta	Eta-Squared
Attainment	**8095**	**69.62**	**12.93**	**18.934****	**0.144**	**0.021**
Non-Attainment	**9198**	**66.07**	**11.48**			

***p <0.05 ** p<0.01**

As Table 4.8 shows (t(d.f. = 16311)=18.934, $p < 0.001$), schools located within attainment areas (M=69.62) were statistically more likely to have a higher percentage of students passing Body Fat fitness testing than were schools in Non-Attainment areas (M=66.07). Thus, this hypothesis was supported. An analysis of association using eta (η=0.144) indicated a very weak positive relationship between $PM_{2.5}$ attainment status and Body Fat, according to Frankfort-Nachmias and Leon-Guerrero's guidelines (Frankfort-Nachmias and Leon-Guerrero, 2002). Eta squared was used to determine the effect size (η^2 = 0.021). $PM_{2.5}$ attainment status explained 2.1% of the variation in Body Fat.

4.2 Specific Aim 2

To examine the association between various demographic factors and measures of aerobic capacity and body composition.

4.2.1 Aerobic Capacity

4.2.1.1 Gender

Prior to the analysis, the independent variable Gender and the dependent variable Aerobic Capacity (AerCap) were screened for accuracy and the assumptions of a t-test. First, the data were screened for missing values. Both Gender and Aerobic Capacity were determined to have no missing data.

Next, the data were screened for univariate outliers using descriptive statistics, stem and leaf plots, and boxplots. All values of Gender were within range, so no data were out of range. Gender was within the requirements of the below than 90%/10% split. Therefore, it did not have univariate outliers. Because the analysis involved grouped data, Aerobic Capacity was split by Gender so that each group could be assessed. Values for each group were within range and the means and standard deviations appeared plausible. Stem and leaf plots and boxplots for both the Female and Male subgroups indicated no outliers. No outlier treatment was necessary.

Then, data were screened for univariate normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms indicated a slight negative skew for both Female and Male groups, but distributions were unimodal. The Q-Q plots each showed little skew for Female and Male.

Descriptive statistics were generated next for each group. The skewness of -0.474 for Females and -0.465 for Males were both within the benchmark levels of $\pm$1.0. The kurtosis of -0.585 for

Females and -0.161 for Males were within the kurtosis benchmark of ±2.0. Thus, the assumption of a normal distribution was satisfied and no further transformations were required.

The final assumption for a t-test is homogeneity of variance, which was assessed with boxplots and Levene's Test for Equality of Variances. The Male box portion of the plot was slightly smaller than the Female box, indicating less variation. The more precise Levene's Test resulted in a p-value of <0.001, indicating the variances were not equal. Thus, the assumption of homogeneity of variance was not satisfied.

The hypothesis predicted that Aerobic Capacity would differ by Gender. Descriptive statistics were generated (Table 4.9). The mean Aerobic Capacity for Females was 61.93 and was absolutely larger than the mean value for Males of 58.10.

A t-test was used to determine whether the two means were statistically different. Because the hypothesis was non-directional, a two-tailed test was used. Alpha was set at 0.05.

Table 4.9
T-test Comparing Aerobic Capacity by Gender

Level	**N**	**Mean**	**S.D.**	**T**	**Eta**	**Eta-Squared**
Female	**16083**	**61.93**	**24.48**	**15.032****	**0.083**	**0.007**
Male	**16372**	**58.10**	**21.22**			

$*p <0.05$ $**p<0.01$

As Table 4.9 shows (t(d.f. = 31644)=15.032, p <0.001), Females (M=61.93) were statistically more likely to have a higher percentage of pass rates in Aerobic Capacity fitness testing than were Males (M=58.10). Thus, this hypothesis was supported. An analysis of association using eta (η=0.083) indicated a very weak positive relationship between Gender and Aerobic Capacity, according to Frankfort-Nachmias and Leon-Guerrero's guidelines (Frankfort-Nachmias and Leon-

Guerrero, 2002). Eta squared was used to determine the effect size ($\eta^2 = 0.007$). Gender explained 0.7% of the variation in Aerobic Capacity.

4.2.1.2 Grade

Prior to the analysis, the independent variable Grade and the dependent variable Aerobic Capacity (AerCap) were screened for accuracy and the assumptions of an ANOVA test. First, the data were screened for missing values. Both Grade and Aerobic Capacity were determined to have no missing data.

Next, the data were screened for univariate outliers using descriptive statistics, stem and leaf plots, and boxplots. All values of Grade were within range, so no data were out of range. Grade was within the requirements of the below than 90%/10% split. Therefore, it did not have univariate outliers. Because the analysis involved grouped data, Aerobic Capacity was split by Grade (5^{th}, 7^{th} and 9^{th}) so that each group could be assessed. Values for each group were within range and the means and standard deviations appeared plausible. Stem and leaf plots and boxplots for the three grade levels indicated no outliers. No outlier treatment was necessary.

Then, data were screened for univariate normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms indicated a slight negative skew for the various grades, but distributions were unimodal. The Q-Q plots each showed little skew for the grades.

Descriptive statistics were assessed next (Table 4.10). Aerobic Capacity for 5^{th} Grade has a skewness of -0.491, which is within the standard of $\pm$1.0. Its kurtosis was -0.355, which is within the standard of $\pm$2.0. Aerobic Capacity for 7^{th} Grade has a skewness of -0.579, which is within the standard of $\pm$1.0. Its kurtosis was -0.191, which is within the standard of $\pm$2.0. Aerobic Capacity for 9^{th} Grade has a skewness of -0.313, which is within the standard of $\pm$1.0. Its kurtosis was -0.708, which is within the standard of $\pm$2.0. Consequently, the assumption of univariate normality has been satisfied for fifth, seventh and ninth grade within Aerobic Capacity and no further transformations were necessary.

Table 4.10
Descriptive Statistics of Aerobic Capacity by Grade

Level	N	Mean	S.D.
5th Grade	10527	61.70	21.70
7th Grade	4037	59.77	21.84
9th Grade	2729	47.67	23.57
Total	17,293	59.03	22.59

The final assumption for a one-way ANOVA is homogeneity of variance, which was assessed with boxplots and Levene's Test for Equality of Variances. The heights of the boxplots indicated some difference in variance. The more precise Levene's Test resulted in a p-value of <0.001, confirming that the variances were not equal. Thus, the assumption of homogeneity of variance was not satisfied. Violation of homogeneity of variance was dealt with by using an alpha of 0.01 rather than 0.05 in subsequent ANOVA testing according to Tabachnick and Fidell (1996).

The hypothesis predicted that Aerobic Capacity would vary by Grade. A One-Way Analysis of Variance was conducted because more than two means were compared. As Table 4.11 indicates, at least one of the means was significantly different (F(d.f. 2, 17290)=442.17, p<0.001). Thus the hypothesis was supported.

Table 4.11
One-way ANOVA for Aerobic Capacity by Grade

Source	SS	DF	MS	F	Eta	Eta-Squared
Between	429,521	2	214,761	442.17**	0.221	0.049
Within	8,397,716	17290	486			
Total	8,827,238	17292				

*p <0.05 ** p<0.01

As Table 4.12 shows, a post-hoc test using the Tukey-Kramer Method ($p<0.001$) indicated that each Grade was significantly different from one another, with 5th grade having a higher overall mean, followed by 7th grade and then 9th grade.

Table 4.12
Tukey-Kramer Multiple Comparison Test for Aerobic Capacity by Grade

Mean	**Aerobic Capacity**	**5th**	**7th**	**9th**
61.43	**5th**		**	**
59.32	**7th**			**
46.93	**9th**			

***p <0.05 ** p<0.01**

Finally, an analysis of association was conducted to determine the strength of association and the effect size. As Table 4.11 shows, eta ($\eta = 0.221$) indicated a weak positive relationship between Grade and Aerobic Capacity, according to Frankfort-Nachmias and Leon-Guerrero's guidelines (Frankfort-Nachmias and Leon-Guerrero, 2002). Eta squared was used to determine the effect size ($\eta^2 = 0.049$). Thus, Grade explained 4.9% of the variation in Aerobic Capacity.

4.2.1.3 Socioeconomic Status

Prior to the analysis, the independent variable SES Quartile (SESQuartile) and the dependent variable Aerobic Capacity (AerCap) were screened for accuracy and the assumptions of an ANOVA test. First, the data were screened for missing values. Aerobic Capacity had no missing data, and SES Quartile had 418 missing data points representing 2.4% of the data set. Because the amount of missing data was less than 5%, Listwise deletion was used.

Next, the data were screened for univariate outliers using descriptive statistics, stem and leaf plots, and boxplots. All values of SES Quartile were within range, so no data were out of range. SES Quartile was within the requirements of the below than 90%/10% split. Therefore, it did not have univariate outliers. Because the analysis involved grouped data, Aerobic Capacity was split by SES Quartile (1st, 2nd, 3rd, and 4th) so that each group could be assessed. Values for each group were within range and the means and standard deviations appeared plausible. Stem and leaf plots and boxplots for the SES Quartiles determined the presence of several outliers in the first SES Quartile. These were confirmed by z-scores outside the allowable $\pm$ 3.0 for cases with Aerobic Capacity values of less than 13.5%. Therefore, these cases were Winsorized and replaced by a value of 14.5%. No outlier treatment was necessary for the remaining Quartiles.

Then, data were screened for univariate normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms indicated a slight negative skew for the various quartiles, but distributions were unimodal. The Q-Q plots each showed little skew for each quartile.

Descriptive statistics were assessed next (Table 4.13). For the 1st Quartile SES within Aerobic Capacity, the skewness of -1.048 is above the standard of $\pm$ 1.0, and the kurtosis is an acceptable 0.841. Because our standard for skewness is conservative and the central theorem applies based on the size of the dataset, the data were not further transformed.

Table 4.13
Descriptive Statistics of Aerobic Capacity by SES Quartile

Level	N	Mean	S.D.
1st Quartile	4104	71.42	18.78
2nd Quartile	3680	60.62	20.51
3rd Quartile	4274	54.03	21.29
4th Quartile	4817	53.46	22.51
Total	16,875	59.53	22.13

Aerobic Capacity for the 2nd Quartile SES has a skewness of -0.591, which is within the standard of $\pm$1.0. Its kurtosis was 0.049, which is within the standard of $\pm$2.0. Aerobic Capacity for the 3rd Quartile SES has a skewness of -0.344, which is within the standard of $\pm$1.0. Its kurtosis was -

0.317, which is within the standard of ±2.0. Aerobic Capacity for the 4th Quartile SES has a skewness of -0.224, which is within the standard of ±1.0. Its kurtosis was -0.549, which is within the standard of ±2.0. Consequently, the assumption of univariate normality has been satisfied for all SES Quartiles within Aerobic Capacity and no further transformations are necessary.

The final assumption for a one-way ANOVA is homogeneity of variance, which was assessed with boxplots and Levene's Test for Equality of Variances. The heights of the boxplots indicated some difference in variance. The more precise Levene's Test resulted in a p-value of <0.001, confirming that the variances were not equal. Thus, the assumption of homogeneity of variance was not satisfied. Violation of homogeneity of variance was dealt with by using an alpha of 0.01 rather than 0.05 in subsequent ANOVA testing according to Tabachnick and Fidell (1996).

The hypothesis predicted that Aerobic Capacity would vary by SES Quartile. A One-Way Analysis of Variance was conducted because more than two means were compared. As Table 4.14 indicates, at least one of the means was significantly different (F(d.f. 3, 16871)=679.98, p<0.001). Thus the hypothesis was supported.

Table 4.14
One-way ANOVA for Aerobic Capacity by SES Quartile

Source	SS	DF	MS	F	Eta	Eta-Squared
Between	**891,188**	**3**	**297063**	**679.98****	**0.328**	**0.108**
Within	**7,370,460**	**16871**	**437**			
Total	**8, 261,648**	**16874**				

***p <0.05 ** p<0.01**

As Table 4.15 shows, a post-hoc test using the Tukey-Kramer Method (p<0.001) indicated that each SES Quartile was significantly different from one another, with the exception of the 3rd and 4th Quartile. The 1st Quartile had a higher overall mean, followed by the 2nd, 3rd, and 4th Quartiles, respectively.

Table 4.15
Tukey-Kramer Multiple Comparison Test for Aerobic Capacity by SES Quartile

Mean	Aerobic Capacity	1st	2nd	3rd	4th
71.42	1st Quartile		**	**	**
60.62	2nd Quartile			**	**
54.03	3rd Quartile				
53.46	4th Quartile				

***p <0.05 ** p<0.01**

Finally, an analysis of association was conducted to determine the strength of association and the effect size. As Table 2 shows, eta ($\eta = 0.328$) indicated a weak positive relationship between Grade and Aerobic Capacity, according to Frankfort-Nachmias and Leon-Guerrero's guidelines (Frankfort-Nachmias and Leon-Guerrero, 2002). Eta squared was used to determine the effect size ($\eta^2 = 0.108$). Thus, Grade explained 10.8% of the variation in Aerobic Capacity.

4.2.1.4 Ethnicity

Prior to the analysis, the independent variable Ethnicity and the dependent variable Aerobic Capacity (AerCap) were screened for accuracy and the assumptions of an ANOVA test. First, the data were screened for missing values. Both Ethnicity and Aerobic Capacity were determined to have no missing data.

Next, the data were screened for univariate outliers using descriptive statistics, stem and leaf plots, and boxplots. All values of Ethnicity were within range, so no data were out of range. The splits range from 0.1% of the dataset (Samoan) to 36.6% of the dataset (Hispanic or Latino). This is outside the desired range of below 90/10 in many cases, so the data were consolidated to improve these ratios. Chinese, Japanese, Korean, Vietnamese, Asian Indian, Laotian, Cambodian and Other Asian records were consolidated into an ethnicity category titled Asian. Samoan and Other Pacific Islander records were consolidated into a category entitled Pacific Islander. All other categories were unchanged. Although the percentage of cases in several of the groups (e.g., American Indian and Pacific Islander) are still quite low, overall the ethnicity categories are more robust for statistical testing.

Because the analysis involved grouped data, Aerobic Capacity was split by Ethnicity (Asian, Hispanic, Black, White (not of Hispanic Origin), Pacific Islander, Filipino and American Indian) so that each group could be assessed. Values for each group were within range and the means and standard deviations appeared plausible. Stem and leaf plots and boxplots indicated several extreme outliers for Asian and Filipino ethnicities within the Aerobic Capacity dataset. They were determined to be accurate values that were part of the desired population samples. Consequently, their influence was reduced by replacing them with the highest value that was not an outlier plus one within each data set, a process called windsorizing. For Asians, those records with an Aerobic Capacity of < 5.6% were replaced with a value of 6.6%. For Filipinos, those records with an Aerobic Capacity of < 3.7% were replaced with a value of 4.7%. No univariate outliers were identified for the other ethnicities that were evaluated; therefore no actions were necessary for these subsets.

Then, data were screened for univariate normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms for all ethnicities indicated unimodal, normal distributions. The Q-Q Probability Plot for each ethnicity indicated little skew.

Descriptive statistics were assessed next (Table 4.16). Aerobic Capacity for the Asian subgroup has a skewness of -0.752, which is within the standard of $\pm$1.0. Its kurtosis was -0.065, which is within the standard of $\pm$2.0. Aerobic Capacity for the Hispanic or Latino subgroup has a skewness of -0.382, which is within the standard of $\pm$1.0. Its kurtosis was -0.338, which is within the standard of $\pm$2.0. Aerobic Capacity for the African American or Black subgroup has a skewness of -0.176, which is within the standard of $\pm$1.0. Its kurtosis was -0.547, which is within the standard of $\pm$2.0. Aerobic Capacity for the White (not of Hispanic Origin) subgroup has a skewness of -0.584, which is within the standard of ±1.0. Its kurtosis was -0.229, which is within the standard of ±2.0. Aerobic Capacity for the Pacific Islander subgroup has a skewness of -0.216, which is within the standard of ±1.0. Its kurtosis was -0.386, which is within the standard of ±2.0. Aerobic Capacity for the Filipino subgroup has a skewness of -0.516, which is within the standard of ±1.0. Its kurtosis was -0.255, which is within the standard of ±2.0. Aerobic Capacity for the American Indian subgroup has a skewness of -0.025, which is within the standard of ±1.0. Its kurtosis was -0.617, which is within the standard of ±2.0. Consequently, the assumption of univariate normality has been satisfied for all Ethnicities within Aerobic Capacity and no further transformations are necessary.

Table 4.16
Descriptive Statistics of Aerobic Capacity by Ethnicity

Level	N	Mean	S.D.
Asian	**4697**	**70.14**	**21.50**
Hispanic	**13683**	**57.48**	**21.87**
Black	**4858**	**53.09**	**22.15**
White	**11323**	**62.78**	**21.92**
Pacific Islander	**97**	**44.67**	**19.72**
Filipino	**1778**	**63.58**	**20.56**
American Indian	**220**	**51.23**	**21.11**
Not Identified	**714**	**61.68**	**23.85**
Total	**37370**	**60.41**	**22.42**

The final assumption for a one-way ANOVA is homogeneity of variance, which was assessed with boxplots and Levene's Test for Equality of Variances. The heights of the boxplots indicated some difference in variance. The more precise Levene's Test resulted in a p-value of <0.001, confirming that the variances were not equal. Thus, the assumption of homogeneity of variance was not satisfied. Violation of homogeneity of variance was dealt with by using an alpha of 0.01 rather than 0.05 in subsequent ANOVA testing according to Tabachnick and Fidell (1996).

The hypothesis predicted that Aerobic Capacity would vary by Ethnicity. A One-Way Analysis of Variance was conducted because more than two means were compared. As Table 4.17 indicates, at least one of the means was significantly different (F(d.f. 7, 37362)=283.67, p<0.001). Thus the hypothesis was supported.

Table 4.17
One-way ANOVA for Aerobic Capacity by Ethnicity

Source	SS	DF	MS	F	Eta	Eta-Squared
Between	947509	7	135358	283.67**	0.225	0.050
Within	1.783E7	37362	477			
Total	1.878E7	37369				

*p <0.05 ** p<0.01

As Table 4.18 shows, a post-hoc test using the Tukey-Kramer Method (p<0.001) indicated that the means of the Ethnicities were largely found to be significantly different, with the exception of the comparison between African Americans and American Indians, Whites and Filipinos, and Pacific Islanders and American Indians.

Table 4.18
Tukey-Kramer Multiple Comparison Test for Aerobic Capacity by Ethnicity

Mean	Aerobic Capacity	Asian	Hispanic	African American	White	Pacific Islander	Filipino	Amer. Indian
70.14	Asian		**	**	**	**	**	**
57.48	Hispanic			**	**	**	**	**
53.09	African American				**	**	**	
62.78	White					**		**
44.67	Pacific Islander						**	
63.58	Filipino							**
51.23	American Indian							

*p <0.05 ** p<0.01

Finally, an analysis of association was conducted to determine the strength of association and the effect size. As Table 4.17 shows, eta (η = 0.225) indicated a weak positive relationship between Ethnicity and Aerobic Capacity, according to Frankfort-Nachmias and Leon-Guerrero's guidelines (Frankfort-Nachmias and Leon-Guerrero, 2002). Eta squared was used to determine the effect size (η^2 = 0.050). Thus, Ethnicity explained 5.0% of the variation in Aerobic Capacity.

4.2.2 Body Fat

4.2.2.1 Gender

Prior to the analysis, the independent variable Gender and the dependent variable Body Fat (BodFat) were screened for accuracy and the assumptions of a t-test. First, the data were screened for missing values. Both Gender and Body Fat were determined to have no missing data.

Next, the data were screened for univariate outliers using descriptive statistics, stem and leaf plots, and boxplots. All values of Gender were within range, so no data were out of range. Gender was within the requirements of the below than 90%/10% split. Therefore, it did not have univariate outliers. Because the analysis involved grouped data, Body Fat was split by Female status so that each group could be assessed. Values for each group were within range and the means and standard deviations appeared plausible.

The stem and leaf plots and the boxplots for both Female and Male genders within Body Fat indicated multiple outliers at the lower end of the distribution. In addition, several outliers were indicated on the upper end of the distribution for Males. The z-scores for the Attainment and NonAttainment subgroups supported the finding of potential outliers within the lower portions of the dataset as several z-scores were outside the allowable $\pm$3.0. The datasets were treated by performing two repetitions of Windsorization which resulted in values for Body Fat in the Female data set which were less than 37% being replaced with values of 38%. Values for Body Fat in the Male data set which were less than 19.2% were replaced with values of 20.2%.

Then, data were screened for univariate normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms indicated unimodal, normal distributions for both Female and Male groups. The Q-Q plots each showed little skew for Female and Male.

Descriptive statistics were generated next for each group. The skewness of -0.437 for Females and -0.202 for Males were both within the benchmark levels of ±1.0. The kurtosis of 0.215 for Females and 0.174 for Males were within the kurtosis benchmark of ±2.0. Thus, the assumption of a normal distribution was satisfied and no further transformations were required.

The final assumption for a t-test is homogeneity of variance, which was assessed with boxplots and Levene's Test for Equality of Variances. The Male box portion of the plot was slightly smaller than the Female box, indicating less variation. The more precise Levene's Test resulted in a p-value of <0.001, indicating the variances were not equal. Thus, the assumption of homogeneity of variance was not satisfied. The violation was dealt with by using the alternative test that compensates for the violation.

The hypothesis predicted that Body Fat would differ by Gender. Descriptive statistics were generated. The mean Body Fat for Females was 75.19 and was absolutely larger than the mean value for Males of 60.97.

A t-test was used to determine whether the two means were statistically different. Because the hypothesis was non-directional, a two-tailed test was used. Alpha was set at 0.05.

Table 4.19
T-test Comparing Body Fat by Gender

Level	N	Mean	S.D.	T	Eta	Eta-Squared
Female	**16083**	**75.19**	**12.54**	**96.843****	**0.473**	**0.224**
Male	**16372**	**60.97**	**13.89**			

***p <0.05 ** p<0.01**

A t-test was conducted because two means were compared. As Table 4.19 shows (t(d.f. = 32227)=96.843, p <0.001), Females (M=75.19) were statistically more likely to have a higher percentage of pass rates in Body Fat fitness testing than were Males (M=60.97). Thus, this hypothesis was supported. An analysis of association using eta (η=0.473) indicated a moderate positive relationship between Gender and Body Fat, according to Frankfort-Nachmias and Leon-Guerrero's guidelines (Frankfort-Nachmias and Leon-Guerrero, 2002). Eta squared was used to determine the effect size ($\eta^2 = 0.224$). Gender explained 22.4% of the variation in Body Fat.

4.2.2.2 Grade

Prior to the analysis, the independent variable Grade and the dependent variable Body Fat (BodFat) were screened for accuracy and the assumptions of an ANOVA test. First, the data were screened for missing values. Both Grade and Body Fat were determined to have no missing data.

Next, the data were screened for univariate outliers using descriptive statistics, stem and leaf plots, and boxplots. All values of Grade were within range, so no data were out of range. Grade was within the requirements of the below than 90%/10% split. Therefore, it did not have univariate outliers. Because the analysis involved grouped data, Body Fat was split by Grade (5^{th}, 7^{th} and 9^{th}) so that each group could be assessed. Values for each group were within range and the means and standard deviations appeared plausible. The z-scores for the 5^{th} Grade subgroup support the finding of potential outliers within the dataset as the z-score is outside the allowable ± 3.0. The dataset was Winsorized twice to reduce the influence of the outliers by replacing all Body Fat passing rate values of less than 31.8% with a value of 32.8%. The stem and leaf plot and the boxplot indicated multiple outliers at the lower and upper end of the distribution. The z-scores for the 7th Grade subgroup support the finding of potential outliers within the dataset on the lower end as the z-score is outside the allowable ± 3.0. The dataset was Winsorized twice to reduce the influence of the outliers by replacing all Body Fat passing rate values of less than 30% with a value of 31%. The stem and leaf plot and the boxplot indicated multiple outliers at the lower and upper end of the distribution. The z-scores for the 9th Grade subgroup support the finding of potential outliers within the dataset on the lower end as the z-score is outside the allowable ± 3.0. The dataset was Winsorized twice to reduce the influence of the outliers by replacing all Body Fat passing rate values of less than 25% with a value of 26%.

Then, data were screened for univariate normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histogram for 5th Grade indicated a unimodal, normal distribution. The histogram for 7th Grade indicated a slightly skewed distribution, but it was unimodal. The histogram for 9th Grade indicated a slightly skewed distribution, but it was unimodal. The Q-Q Probability Plots for each of the Grades indicated little skew.

Descriptive statistics (Table 4.20) were assessed next. Body Fat for 5th Grade has a skewness of -0.132, which is within the standard of ± 1.0. Its kurtosis was 0.097, which is within the standard of ± 2.0. Body Fat for 7th Grade has a skewness of -0.360, which is within the standard of ± 1.0. Its kurtosis was 0.446, which is within the standard of ± 2.0. Body Fat for 9th Grade has a skewness of -0.748, which is within the standard of ± 1.0. Its kurtosis was 1.033, which is within the standard of ± 2.0. Consequently, the assumption of univariate normality has been satisfied for fifth, seventh and ninth grade within Body Fat and no further transformations are necessary.

Table 4.20
Descriptive Statistics of Body Fat by Grade

Level	N	Mean	S.D.
5th Grade	10527	68.23	12.07
7th Grade	4037	67.12	12.31
9th Grade	2729	66.55	13.57
Total	17,293	67.71	12.39

The final assumption for a one-way ANOVA is homogeneity of variance, which was assessed with boxplots and Levene's Test for Equality of Variances. The heights of the boxplots indicated some difference in variance. The more precise Levene's Test resulted in a p-value of <0.001, confirming that the variances were not equal. Thus, the assumption of homogeneity of variance was not satisfied. Violation of homogeneity of variance was dealt with by using an alpha of 0.01 rather than 0.05 in subsequent ANOVA testing according to Tabachnick and Fidell (1996).

The hypothesis predicted that Body Fat would vary by Grade. A One-Way Analysis of Variance was conducted because more than two means were compared. As Table 4.21 indicates, at least one of the means was significantly different (F(d.f. 2, 7874)=25.715, p<0.001). Thus the hypothesis was supported.

Table 4.21
One-way ANOVA for Body Fat

Source	SS	DF	MS	F	Eta	Eta-Squared
Between	7873.7	2	3937	25.715**	0.054	0.003
Within	2,647,040	17290	153			
Total	2,654,913	17292				

***p <0.05 ** p<0.01**

As Table 4.22 shows, a post-hoc test using the Tukey-Kramer Method indicated that the mean of 5th Grade was significantly different ($p<0.001$) than 7th and 9th Grades. The mean for 5th Grade was 1.11 higher than the mean for 7th Grade and 1.67 higher than the mean for 9th Grade. The mean for 7th Grade and 9th Grade was not significantly different ($p=0.155$) with an overall difference of 0.57, with 7th grade being higher.

Table 4.22
Tukey-Kramer Multiple Comparison Test for Body Fat by Grade

Mean	**Body Fat**	**5th**	**7th**	**9th**
68.23	**5th**		**	**
67.12	**7th**			
66.55	**9th**			

***p <0.05 ** p<0.01**

Finally, an analysis of association was conducted to determine the strength of association and the effect size. As Table 4.21 shows, eta ($\eta = 0.054$) indicated a weak positive relationship between Grade and Body Fat, according to Frankfort-Nachmias and Leon-Guerrero's guidelines (Frankfort-Nachmias and Leon-Guerrero, 2002). Eta squared was used to determine the effect size ($\eta^2 = 0.003$). Thus, Grade explained 0.3% of the variation in Body Fat.

4.2.2.3 SES Quartile

Prior to the analysis, the independent variable SES Quartile (SESQuartile) and the dependent variable Body Fat (BodFat) were screened for accuracy and the assumptions of an ANOVA test. First, the data were screened for missing values. Body Fat had no missing data, and SES Quartile had 418 missing data points representing 2.4% of the data set. Because the amount of missing data was less than 5%, Listwise deletion was used.

Next, the data were screened for univariate outliers using descriptive statistics, stem and leaf plots, and boxplots. All values of SES Quartile were within range, so no data were out of range. SES Quartile was within the requirements of the below than 90%/10% split. Therefore, it did not have univariate outliers. Because the analysis involved grouped data, Body Fat was split by SES Quartile (1st, 2nd, 3rd, and 4th) so that each group could be assessed. Values for each group were within range and the means and standard deviations appeared plausible. For the 1st SES Quartile, the stem and leaf plot and the boxplot indicated multiple outliers at the lower end of the distribution. The z-scores for the 1st Quartile subgroup support the finding of potential outliers within the dataset as the z-score is outside the allowable $\pm$3.0. The dataset was Winsorized three times to reduce the influence of the outliers by replacing all Body Fat passing rate values of less than 48.5% with a value of 49.5%. For the 2nd SES Quartile, the stem and leaf plot and the boxplot indicated multiple outliers at the lower end of the distribution. The z-scores for the 2nd Quartile subgroup support the finding of potential outliers within the dataset as the z-score is outside the allowable $\pm$3.0. The dataset was Winsorized three times to reduce the influence of the outliers by replacing all Body Fat passing rate values of less than 40.9% with a value of 41.9% and replacing all Body Fat passing rate values of greater than 98.8% with a value of 97.8%. For the 3rd SES Quartile, the stem and leaf plot and the boxplot indicated multiple outliers at the lower end of the distribution. The z-scores for the 3rd Quartile subgroup support the finding of potential outliers within the dataset as the z-score is outside the allowable $\pm$3.0. The dataset was Winsorized three times to reduce the influence of the outliers by replacing all Body Fat passing rate values of less than 34.1% with a value of 35.1% and replacing all Body Fat passing rate values of greater than 94.6% with a value of 93.6%. For the 4th SES Quartile, the stem and leaf plot and the boxplot indicated multiple outliers at the lower end of the distribution. The z-scores for the 4th Quartile subgroup support the finding of potential outliers within the dataset as the z-score is outside the allowable $\pm$3.0. The dataset was Winsorized three times to reduce the influence of the outliers by replacing all Body Fat passing rate values of less than 30.8% with a value of 31.8% and replacing all Body Fat passing rate values of greater than 91.10% with a value of 90.10%.

Univariate normality was assessed for Body Fat in the SES Quartile Groups. The assumption was first visually assessed using graphs. The histograms for each Quartile indicated unimodal, normal distributions. The Q-Q Probability Plot for each quartile indicated little skew.

Descriptive statistics (Table 4.23) were assessed next. Body Fat for the 1st Quartile SES has a skewness of -0.760, which is within the standard of $\pm$1.0. Its kurtosis was 0.879, which is within the standard of $\pm$2.0. Body Fat for the 2nd Quartile SES has a skewness of -0.437, which is within the standard of $\pm$1.0. Its kurtosis was 0.956, which is within the standard of $\pm$2.0. Body Fat for the 3rd Quartile SES has a skewness of -0.314, which is within the standard of $\pm$1.0. Its kurtosis was 1.030, which is within the standard of $\pm$2.0. Body Fat for the 4th Quartile SES has a skewness of 0.048, which is within the standard of $\pm$1.0. Its kurtosis was 1.037, which is within the standard of $\pm$2.0. Consequently, the assumption of univariate normality has been satisfied for all SES Quartiles within Body Fat and no further transformations are necessary.

Table 4.23
Descriptive Statistics of Body Fat by SES Quartile

Level	N	Mean	S.D.
1st Quartile	4104	77.85	9.61
2nd Quartile	3680	69.95	9.59
3rd Quartile	4274	64.36	10.12
4th Quartile	4817	60.79	10.10
Total	16,875	67.84	11.84

The final assumption for a one-way ANOVA is homogeneity of variance, which was assessed with boxplots and Levene's Test for Equality of Variances. The heights of the boxplots indicated some difference in variance. The more precise Levene's Test resulted in a p-value of 0.058, confirming that the variances were equal. Thus, the assumption of homogeneity of variance was satisfied.

The hypothesis predicted that Body Fat would vary by SES Quartile. A One-Way Analysis of Variance was conducted because more than two means were compared. As Table 4.24 indicates, at least one of the means was significantly different (F(d.f. 3, 16871)=2457, p<0.001). Thus, the hypothesis was supported.

Table 4.24
One-way ANOVA for Body Fat by SES Quartile

Source	SS	DF	MS	F	Eta	Eta-Squared
Between	719,053	3	239,684	2457**	0.551	0.304
Within	1,645,994	16871	98			
Total	2,365,947	16874				

***p <0.05 ** p<0.01**

As Table 4.25 shows, a post-hoc test using the Tukey-Kramer Method (p<0.001) indicated that each SES Quartile was significantly different from one another. The 1st Quartile had a higher overall mean, followed by the 2nd, 3rd, and 4th Quartiles, respectively.

Table 4.25
Tukey-Kramer Multiple Comparison Test for Body Fat by SES Quartile

Mean	Body Fat	1st	2nd	3rd	4th
77.85	1st Quartile		**	**	**
69.95	2nd Quartile			**	**
64.36	3rd Quartile				**
60.79	4th Quartile				

***p <0.05 ** p<0.01**

Finally, an analysis of association was conducted to determine the strength of association and the effect size. As Table 4.24 shows, eta (η = 0.551) indicated a weak positive relationship between Grade and Body Fat, according to Frankfort-Nachmias and Leon-Guerrero's guidelines (Frankfort-Nachmias and Leon-Guerrero, 2002). Eta squared was used to determine the effect size (η^2 = 0.304). Thus, Grade explained 30.4% of the variation in Body Fat.

4.2.2.4 Ethnicity

Prior to the analysis, the independent variable Ethnicity and the dependent variable Body Fat (BodFat) were screened for accuracy and the assumptions of an ANOVA test. First, the data were screened for missing values. Both Ethnicity and Body Fat were determined to have no missing data.

Next, the data were screened for univariate outliers using descriptive statistics, stem and leaf plots, and boxplots. All values of Ethnicity were within range, so no data were out of range. The splits range from 0.1% of the dataset (Samoan) to 36.6% of the dataset (Hispanic or Latino). This is outside the desired range of below 90/10 in many cases, so the data were consolidated to improve these ratios. Chinese, Japanese, Korean, Vietnamese, Asian Indian, Laotian, Cambodian and Other Asian records were consolidated into an ethnicity category titled Asian. Samoan and Other Pacific Islander records were consolidated into a category entitled Pacific Islander. All other categories were unchanged. Although the percentage of cases in several of the groups (e.g., American Indian and Pacific Islander) are still quite low, overall the ethnicity categories are more robust for statistical testing.

Because the analysis involved grouped data, Aerobic Capacity was split by Ethnicity (Asian, Hispanic, Black, White (not of Hispanic Origin), Pacific Islander, Filipino and American Indian) so that each group could be assessed. Values for each group were within range and the means and standard deviations appeared plausible. Stem and leaf plots and boxplots indicated several extreme outliers for Asian, Hispanic, African American or Black, White (not of Hispanic Origin) and Filipino ethnicities within the Body Fat dataset. They were determined to be accurate values that were part of the desired population samples. Consequently, their influence was reduced by replacing them with the highest value that was not an outlier plus one within each data set, a process called windsorizing. The z-scores for the Asian subgroup support the finding of potential outliers within the dataset as the z-score is outside the allowable $\pm$3.0, for cases with Body Fat values of less than 45.5%. Therefore, these cases were Winsorized and replaced by a value of 46.5%. The z-scores for the Hispanic subgroup support the finding of potential outliers within the dataset as the z-score is outside the allowable $\pm$3.0, for cases with Body Fat values of less than 26.8% or higher than 97.2%. Therefore, these cases were Winsorized and replaced by values of 27.8% and 96.2%, respectively. The z-scores for the African American subgroup support the finding of potential outliers within the dataset as the z-score is outside the allowable $\pm$3.0, for cases with Body Fat values of less than 28.6%. Therefore, these cases were Winsorized and replaced by a value of 29.6%. The z-scores for the White subgroup support the finding of potential outliers within the dataset as the z-score is outside the allowable $\pm$3.0, for cases with Body Fat values of less than 37.5%. Therefore, these cases were Winsorized and replaced by a value of 38.5%. The z-scores for the Filipino subgroup support the finding of potential outliers within the dataset as the z-score is outside the allowable $\pm$3.0, for cases with Body Fat values of less than 37.4%. Therefore, these cases were Winsorized and replaced by a value of 38.4%. No univariate outliers were identified for Pacific Islanders or American Indians; therefore no actions were necessary for these subsets.

Then, data were screened for univariate normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms for all ethnicities indicated unimodal, normal distributions. The Q-Q Probability Plot for each ethnicity indicated little skew.

Descriptive statistics (Table 4.26) were assessed next. Body Fat for the Asian subgroup has a skewness of -0.648, which is within the standard of $\pm$1.0. Its kurtosis was 0.227, which is within the standard of $\pm$2.0. Body Fat for the Hispanic or Latino subgroup has a skewness of 0.007, which is within the standard of $\pm$1.0. Its kurtosis was 0.716, which is within the standard of $\pm$2.0. Body Fat for the African American or Black subgroup has a skewness of -0.268, which is within the standard of $\pm$1.0. Its kurtosis was 0.335, which is within the standard of $\pm$2.0. Body Fat for the White (not of Hispanic Origin) subgroup has a skewness of -0.680, which is within the standard of +1.0. Its kurtosis was 0.484, which is within the standard of +2.0. Body Fat for the Pacific Islander subgroup has a skewness of -0.123, which is within the standard of +1.0. Its kurtosis was -0.742, which is within the standard of +2.0. Body Fat for the Filipino subgroup has a skewness of -0.368, which is within the standard of +1.0. Its kurtosis was 0.169, which is within the standard of +2.0. Body Fat for the American Indian subgroup has a skewness of -0.048, which is within the standard of +1.0. Its kurtosis was -0.375, which is within the standard of +2.0. Consequently, the assumption of univariate normality has been satisfied for all Ethnicities within Body Fat and no further transformations are necessary.

Table 4.26
Descriptive Statistics of Body Fat by Ethnicity

Level	N	Mean	S.D.
Asian	**4697**	**80.22**	**11.65**
Hispanic	**13683**	**62.03**	**11.69**
Black	**4858**	**66.63**	**12.75**
White	**11323**	**74.33**	**12.13**
Pacific Islander	**97**	**54.56**	**19.36**
Filipino	**1778**	**72.84**	**11.88**
American Indian	**220**	**60.84**	**15.57**
Total	**37370**	**69.28**	**13.84**

The final assumption for a one-way ANOVA is homogeneity of variance, which was assessed with boxplots and Levene's Test for Equality of Variances. The heights of the boxplots indicated some difference in variance. The more precise Levene's Test resulted in a p-value of <0.001, confirming that the variances were not equal. Thus, the assumption of homogeneity of variance was not satisfied. Violation of homogeneity of variance was dealt with by using an alpha of 0.01 rather than 0.05 in subsequent ANOVA testing according to Tabachnick and Fidell (1996).

The hypothesis predicted that Body Fat would vary by Ethnicity. A One-Way Analysis of Variance was conducted because more than two means were compared. As Table 4.27 indicates, at least one of the means was significantly different (F(d.f. 7, 37362)=1606, p<0.001). Thus the hypothesis was supported.

Table 4.27
One-way ANOVA for Body Fat by Ethnicity

Source	SS	DF	MS	F	Eta	Eta-Squared
Between	1,655,984	7	236,569	1606**	0.481	0.231
Within	5,503,472	37362	147			
Total	7,159,456	37369				

*p <0.05 ** p<0.01

As Table 4.28 shows, a post-hoc test using the Tukey-Kramer Method demonstrated that the means of all of the Ethnicities were found to be significantly different (p<0.01), with the exception of the comparison between Hispanics and American Indians (p=0.841).

Table 4.28
Tukey-Kramer Multiple Comparison Test for Body Fat by Ethnicity

Mean	Body Fat	Asian	Hispanic	Black	White	Pac Isl	Filipino	Am Ind
80.22	Asian		**	**	**	**	**	**
62.03	Hispanic			**	**	**	**	
66.63	Black				**	**	**	**
74.33	White					**	**	**
54.56	Pacific Islander						**	**
72.84	Filipino							**
60.84	American Indian							

*p <0.05 ** p<0.01

Finally, an analysis of association was conducted to determine the strength of association and the effect size. As Table 4.27 shows, eta (η = 0.481) indicated a weak positive relationship between Ethnicity and Body Fat, according to Frankfort-Nachmias and Leon-Guerrero's guidelines

(Frankfort-Nachmias and Leon-Guerrero, 2002). Eta squared was used to determine the effect size ($\eta^2 = 0.231$). Thus, Ethnicity explained 23.1% of the variation in Body Fat.

4.3 Specific Aim 3

To examine the association between attainment status for CO, O_3, PM_{10}, and $PM_{2.5}$ and aerobic capacity or body composition in children after adjusting for demographic factors that influence these endpoints.

Demographic factors that influenced both aerobic capacity and body fat fitness endpoints were assessed in Specific Aim 2 (Section 4.2). Aerobic Capacity and Body Fat passing rates were found to differ significantly by Gender, Grade, SES, and Ethnicity. Therefore, measures of these variables were incorporated into the regression analyses summarized in this section.

4.3.1 Aerobic Capacity

4.3.1.1 Carbon Monoxide

Prior to the analysis, the independent variables (Grade, BodFat, PctMale, PctSES, PctMinority and COATT) and the dependent variable Aerobic Capacity (AerCap) were screened for accuracy. First, the data were screened for missing values. PctSES was determined to be missing 2.4% of its data, since the percent of free/reduced price meals was unavailable for all schools. Because the percentage of missing data was less than 5%, Listwise deletion was used. No other variables were found to have missing data. All variables were determined to have values within their allowable ranges.

The data were next screened for influential outliers in solution. The maximum for Cook's distance was 0.004, well below the standard of 1.0 for problems. The minimum and maximum Studentized Deleted Residuals were -3.893 and 3.570, indicating that some values are outside the standard of

±3.3. There are 16 values below -3.3 and 3 values greater than 3.3. Therefore, a scatterplot was generated to examine the outliers. The cases were examined to determine why they were outliers in solution. No pattern was detected with the outliers, so they were deleted from further analyses.

The Unstandardized residuals were screened for normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms indicated a unimodal, normal distribution with minimal skew. The Q-Q plot also showed little skew. Descriptive statistics were generated with the skewness of -0.386 for within the benchmark levels of ±1.0. The kurtosis of -0.069 was within the kurtosis benchmark of ±2.0. Thus, the assumption of a normal distribution was satisfied and no further transformations were required.

A scatterplot of standardized residuals against standardized predicted values was used to evaluate both linearity and homoscedasticity. Overall, the data were linear and evenly distributed, satisfying the assumptions of both linearity and homoscedasticity.

A correlation matrix (Table 4.29) was generated and all of the independent variables were significantly correlated ($p<0.001$) with the dependent variable. All of the correlations between IV's are less than 0.70, indicating no multicollinearity. To further explore multicollinearity, measures of tolerance and VIF were evaluated. Tolerance is 0.455 or higher for all variables, so it is well above the 0.20 standard for problems. The highest VIF is 2.197, well below the 4.0 or above standard for problems. Both of the values indicate no multicollinearity

Three regression models were evaluated in this analysis. The first model was between Aerobic Capacity and Carbon Monoxide Attainment status to determine if there was a significant relationship between these two variables. Because Aerobic Capacity may be influenced by several variables, a second model was run to evaluate the relationship between Aerobic Capacity and the independent variables Grade, BodFat, PctMale, PctSES, and PctMinority. The third model investigated whether a relationship between Aerobic Capacity and Carbon Monoxide Attainment Status existed after controlling for the variables in the second model.

Table 4.29
Correlations and Descriptive Statistics

Variables	Aerobic Capacity (DV)	Grade	Bod Fat	PctMale	PctSES	Pct Minority	COATT
AerCap (DV)		-0.186**	0.391**	-0.112**	-0.319**	-0.265**	-0.051**
Grade			-0.046**	0.074**	-0.122**	-0.047**	-0.031**
BodFat				-0.100**	-0.491**	-0.428**	-0.050**
PctMale					0.020**	-0.002	-0.006
PctSES						0.698**	0.079**
PctMinority							0.168**
COATT							
Mean	59.55	6.07	67.45	51.44	52.45	67.70	0.19
S.D.	22.14	1.49	13.23	7.54	29.70	27.70	0.394

***p <0.05 ** p<0.01**

Durbin-Watson was used to test for intercorrelation in the models. This value is 1.589 for the single independent variable model, and 1.77 for the multivariable models. These values are within the range of 1.0 to 3.0 so no intercorrelation exists.

Model 1

For the first model, a standard regression was conducted to determine the relationship between Aerobic Capacity and Carbon Monoxide Attainment Status. Alpha was set at 0.05. The results indicate ($F(1, 16854) = 44.1$, $p<0.001$) that Carbon Monoxide Attainment status is significantly related to Aerobic Capacity.

Table 4.30
Model 1: Standard Regression of COATT for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
COATT	-2.869**	-0.051	0.003	0.051	0.003	0.003
	Intercept = 60.1					

*p <0.05 ** p<0.01

As the regression coefficients in Table 4.30 indicate, Carbon Monoxide Attainment status contributed significantly to Aerobic Capacity. The multiple correlation (R=0.051) indicated a very weak positive relationship between Carbon Monoxide Attainment Status and Aerobic Capacity. Overall, the model (R^2=0.003) explained 0.3% of the variation in Aerobic Capacity.

<u>Model 2</u>

For the second model, a standard regression was conducted to determine the relationship between Aerobic Capacity and several non-environmental variables (Grade, BodFat, PctMale, PctSES, PctMinority) that may influence this endpoint. Alpha was set at 0.05. The results indicate (F(5, 16850) = 932, p<0.001) that at least one of the variables is significantly related to Aerobic Capacity.

As the regression coefficients in Table 4.31 indicate, all variables contributed significantly to Aerobic Capacity. Beta weights indicate that Body Fat (β=0.271) was the strongest unique predictor, followed by Grade (β=-0.193), PctSES (β=-0.189), PctMale (β=-0.067) and PctMinority (β=-0.026). When only the unique variance explained by each variable is examined, Body Fat (sr^2=0.053) also accounts for the most variance in Aerobic Capacity, 5.3%, followed by Grade (sr^2=0.036) with 3.6%, PctSES (sr^2=0.016) with 1.6%, PctMale (sr^2=0.005) with 0.5%, and PctMinority (sr^2=0.0003) with 0.03%. Total unique variance was 11%. The zero-order correlations for BodFat, PctMale, PctSES, and PctMinority were higher than their semipartial correlations, indicating shared variance between the variables. However, for Grade the zero-order correlation was slightly lower than the corresponding semipartial correlation, indicating the possible presence of a suppressor variable. The semipartial correlation for PctMinority approaches zero, indicating the possible presence of a spurious or intervening relationship.

Table 4.31
Model 2: Standard Regression of Variables for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	-2.865**	-0.193	0.0357	0.465	0.217	0.216
Body Fat	0.454**	0.271	0.0534			
Pct Male	-0.197**	-0.067	0.0045			
Pct SES	-0.141**	-0.189	0.0164			
Pct Minority	-0.021**	-0.026	0.0003			
	Intercept = 65.24					

*p <0.05 ** p<0.01

The multiple correlation (R=0.465) indicated a moderate positive relationship between the combination of independent variables and Aerobic Capacity. Overall, the model (R^2=0.217) explained 21.7% of the variation in Aerobic Capacity.

Model 3

For the third model, a standard regression was conducted to determine the relationship between Aerobic Capacity and Carbon Monoxide Attainment Status after controlling for the independent variables in Model 2 (Grade, BodFat, PctMale, PctSES, PctMinority). Alpha was set at 0.05. The results indicate (F(6, 16849) = 780, p<0.001) that at least one of the variables is significantly related to Aerobic Capacity.

Table 4.32
Model 3: Standard Regression of Variables (incl. COATT) for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	-2.876**	-0.193	0.0361	0.466	0.217	0.217
Body Fat	0.455**	0.272	0.0538			
Pct Male	-0.197**	-0.067	0.0045			
Pct SES	-0.143**	-0.191	0.0166			
Pct Minority	-0.016*	-0.020	0.0002			
COATT	-1.427**	-0.025	0.0006			
	Intercept = 65.34					

*p <0.05 ** p<0.01

As the regression coefficients in Table 4.32 indicate, all variables contributed significantly to Aerobic Capacity. Beta weights indicate that Body Fat (β=0.272) was the strongest unique predictor, followed by Grade (β=-0.193), PctSES (β=-0.191), PctMale (β=-0.067), Carbon Monoxide Attainment Status (β=-0.025), and PctMinority (β=-0.020). When only the unique variance explained by each variable is examined, Body Fat (sr^2=0.054) also accounts for the most variance in Aerobic Capacity, 5.4%, followed by Grade (sr^2=0.036) with 3.6%, PctSES (sr^2=0.017) with 1.7%, PctMale (sr^2=0.005) with 0.5%, Carbon Monoxide Attainment Status (sr^2=0.0006) with 0.06%, and PctMinority (sr^2=0.0002) with 0.02%. Total unique variance was 11.2%. The zero-order correlations for BodFat, PctMale, PctSES. PctMinority, and Carbon Monoxide Attainment status were higher than their semipartial correlations, indicating shared variance between the variables. However, for Grade the zero-order correlation was slightly lower than the corresponding semipartial correlation, indicating the possible presence of a suppressor variable. The semipartial correlation for PctMinority approaches zero, indicating the possible presence of a spurious or intervening relationship.

The multiple correlation (R=0.466) indicated a moderate positive relationship between the combination of independent variables and Aerobic Capacity. Overall, the model (R^2=0.217) explained 21.7% of the variation in Aerobic Capacity.

The R^2 change between model 2 and model 3 was 0.001, indicating that the inclusion of Carbon Monoxide Attainment status in the model added 0.1% to the explanation of the variance in the model.

4.3.1.2 8-hour Ozone

Prior to the analysis, the independent variables (Grade, BodFat, PctMale, PctSES, PctMinority and O3ATT) and the dependent variable Aerobic Capacity (AerCap) were screened for accuracy. First, the data were screened for missing values. PctSES was determined to be missing 2.4% of its data, since the percent of free/reduced price meals was unavailable for all schools. Because the percentage of missing data was less than 5%, Listwise deletion was used. No other variables were found to have missing data. All variables were determined to have values within their allowable ranges.

The maximum for Cook's distance is 0.004, well below the standard of 1.0 for problems. The minimum and maximum Studentized Deleted Residuals are -3.868 and 3.598. This indicates that some values are outside the standard of $\pm$3.3. There are 14 values below -3.3 and 3 values greater than 3.3. Therefore, we generate a scatterplot to examine the outliers using the values for Studentized Deleted Residuals and Standardized Values. The cases were examined to determine why they were outliers in solution. No pattern was detected with the outliers, so they were deleted from further analyses.

The Unstandardized residuals were screened for normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms indicated a unimodal, normal distribution with minimal skew. The Q-Q plot also showed little skew. Descriptive statistics were generated with the skewness of -0.388 for within the benchmark levels of $\pm$1.0. The kurtosis of -0.065 was within the kurtosis benchmark of $\pm$2.0. Thus, the assumption of a normal distribution was satisfied and no further transformations were required.

A scatterplot of standardized residuals against standardized predicted values was used to evaluate both linearity and homoscedasticity. Overall, the data were linear and evenly distributed, satisfying the assumptions of both linearity and homoscedasticity.

Table 4.33
Correlations and Descriptive Statistics

Variables	Aerobic Capacity (DV)	Grade	BodFat	PctMale	PctSES	O3ATT
AerCap (DV)		-0.186**	0.391**	-0.112**	-0.318**	-0.026**
Grade			-0.046**	0.074**	-0.122**	-0.053**
BodFat				-0.100**	-0.491**	-0.012
PctMale					0.020**	-0.009
PctSES						0.007
O3ATT						
Mean	59.54	6.07	67.45	51.44	52.45	0.91
S.D.	22.15	1.49	13.23	7.54	29.70	0.288

$^*p < 0.05$ $^{**} p < 0.01$

A correlation matrix (Table 4.33) was generated and all of the independent variables were significantly correlated ($p<0.001$) with the dependent variable. All of the correlations between IV's are less than 0.70, indicating no multicollinearity. To further explore multicollinearity, measures of tolerance and VIF were evaluated. Tolerance is 0.437 or higher for all variables, so it is well above the 0.20 standard for problems. The highest VIF is 2.286, well below the 4.0 or above standard for problems. Both of the values indicate no multicollinearity

Three regression models were evaluated in this analysis. The first model was between Aerobic Capacity and Ozone Attainment status to determine if there was a significant relationship between these two variables. Because Aerobic Capacity may be influenced by several variables, a second model was run to evaluate the relationship between Aerobic Capacity and the independent variables Grade, BodFat, PctMale, and PctSES. The third model investigated whether a relationship between Aerobic Capacity and Ozone Attainment Status existed after controlling for the variables in the second model. An evaluation of the significance of the t value found that PctMinority was not significant (p=0.182) when added to the third model. Therefore, it was dropped from analysis in both models.

Durbin-Watson was used to test for intercorrelation in the models. This value is 1.590 for the single independent variable model, and 1.775 for the multivariable models. These values are within the range of 1.0 to 3.0 so no intercorrelation exists.

Model 1

For the first model, a standard regression was conducted to determine the relationship between Aerobic Capacity and Ozone Attainment Status. Alpha was set at 0.05. The results indicate (F(1, 16856) = 11.3, p=0.001) that Ozone Attainment status is significantly related to Aerobic Capacity.

Table 4.34
Model 1: Standard Regression of Ozone Attainment for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
O3ATT	-1.996**	-0.026	0.001	0.026	0.001	0.001
	Intercept = 61.35					

***p <0.05 ** p<0.01**

As the regression coefficients in Table 4.34 indicate, Ozone Attainment status contributed significantly to Aerobic Capacity. The multiple correlation (R=0.026) indicated a very weak positive relationship between Ozone Attainment Status and Aerobic Capacity. Overall, the model (R^2=0.001) explained 0.1% of the variation in Aerobic Capacity.

Model 2

For the second model, a standard regression was conducted to determine the relationship between Aerobic Capacity and several non-environmental variables (Grade, BodFat, PctMale, PctSES) that may influence this endpoint. Alpha was set at 0.05. The results indicate ($F(4, 16870) = 1129$, $p<0.001$) that at least one of the variables is significantly related to Aerobic Capacity.

Table 4.35
Model 2: Standard Regression of Variables for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	-2.874**	-0.193	0.0357	0.459	0.211	0.211
Body Fat	0.446**	0.267	0.0529			
Pct Male	-0.198**	-0.067	0.0045			
Pct SES	-0.155**	-0.208	0.0320			
	Intercept = 65.16					

*p <0.05 ** p<0.01

As the regression coefficients in Table 4.35 indicate, all variables contributed significantly to Aerobic Capacity. Beta weights indicate that Body Fat (β=0.267) was the strongest unique predictor, followed by PctSES (β=-0.208), Grade (β=-0.193), and PctMale (β=-0.067). When only the unique variance explained by each variable is examined, Body Fat (sr^2=0.053) also accounts for the most variance in Aerobic Capacity, 5.3%, followed by Grade (sr^2=0.036) with 3.6%, PctSES (sr^2=0.032) with 3.2%, and PctMale (sr^2=0.005) with 0.5%. Total unique variance was 12.5%. The zero-order correlations for BodFat, PctMale and PctSES were higher than their semipartial correlations, indicating shared variation with the other variables in the model. However, for Grade, the zero-order correlation was slightly lower than the corresponding semipartial correlation, indicating the possible presence of a suppressor variable.

The multiple correlation (R=0.459) indicated a moderate positive relationship between the combination of independent variables and Aerobic Capacity. Overall, the model (R^2=0.211) explained 21.1% of the variation in Aerobic Capacity.

Model 3

For the third model, a standard regression was conducted to determine the relationship between Aerobic Capacity and Ozone Attainment Status after controlling for the independent variables in Model 2 (Grade, BodFat, PctMale, PctSES). Alpha was set at 0.05. The results indicate ($F(5, 16869) = 908$, $p<0.001$) that at least one of the variables is significantly related to Aerobic Capacity.

Table 4.36
Model 3: Standard Regression of Variables (incl. O3ATT) for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	-2.899**	-0.194	0.0365	0.460	0.212	0.212
Body Fat	0.445**	0.266	0.0524			
Pct Male	-0.198**	-0.067	0.0044			
Pct SES	-0.156**	-0.208	0.0320			
O3ATT	-2.380**	-0.031	0.0012			
	Intercept = 67.59					

*p <0.05 ** p<0.01

As the regression coefficients in Table 4.36 indicate, all variables contributed significantly to Aerobic Capacity. Beta weights indicate that Body Fat (β=0.266) was the strongest unique predictor, followed by PctSES (β=-0.208), Grade (β=-0.194), PctMale (β=-0.067), and Ozone Attainment Status (β=-0.031). When only the unique variance explained by each variable is examined, Body Fat (sr^2=0.052) also accounts for the most variance in Aerobic Capacity, 5.2%, followed by Grade (sr^2=0.037) with 3.7%, PctSES (sr^2=0.032) with 3.2%, PctMale (sr^2=0.004) with 0.4%, and Ozone Attainment Status (sr^2=0.001) with 0.1%. Total unique variance was 12.6%. The zero-order correlations for BodFat, PctMale and PctSES were higher than their semipartial correlations, indicating shared variation with the other variables in the model. However, for Grade and Ozone Attainment Status, the zero-order correlations were slightly lower than the corresponding semipartial correlation, indicating the possible presence of a suppressor variable.

The multiple correlation (R=0.460) indicated a moderate positive relationship between the combination of independent variables and Aerobic Capacity. Overall, the model (R^2=0.212) explained 21.2% of the variation in Aerobic Capacity.

The R^2 change between model 2 and model 3 was 0.001, indicating that the inclusion of Ozone Attainment status in the model added 0.1% to the explanation of the variance in the model.

4.3.1.3 PM_{10}

Prior to the analysis, the independent variables (Grade, BodFat, PctMale, PctSES, PctMinority and PM_{10} Attainment Status) and the dependent variable Aerobic Capacity (AerCap) were screened for accuracy. First, the data were screened for missing values. PctSES was determined to be missing 2.4% of its data, since the percent of free/reduced price meals was unavailable for all schools. Because the percentage of missing data was less than 5%, Listwise deletion was used. No other variables were found to have missing data. All variables were determined to have values within their allowable ranges.

The data were next screened for influential outliers in solution. The maximum for Cook's distance was 0.004, well below the standard of 1.0 for problems. The minimum and maximum Studentized Deleted Residuals were -3.901 and 3.551, indicating that some values are outside the standard of $\pm$3.3. There are 15 values below -3.3 and 3 values greater than 3.3. Therefore, a scatterplot was generated to examine the outliers. The cases were examined to determine why they were outliers in solution. No pattern was detected with the outliers, so they were deleted from further analyses.

The Unstandardized residuals were screened for normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms indicated a unimodal, normal distribution with minimal skew. The Q-Q plot also showed little skew. Descriptive statistics were generated with the skewness of -0.387 for within the benchmark levels of $\pm$1.0. The kurtosis of -0.066 was within the kurtosis benchmark of $\pm$2.0. Thus, the assumption of a normal distribution was satisfied and no further transformations were required.

A scatterplot of standardized residuals against standardized predicted values was used to evaluate both linearity and homoscedasticity. Overall, the data were linear and evenly distributed, satisfying the assumptions of both linearity and homoscedasticity.

A correlation matrix (Table 4.37) was generated and all of the independent variables were significantly correlated ($p<0.001$) with the dependent variable. All of the correlations between IV's are less than 0.70, indicating no multicollinearity. To further explore multicollinearity, measures of tolerance and VIF were evaluated. Tolerance is 0.455 or higher for all variables, so it is well above the 0.20 standard for problems. The highest VIF is 2.197, well below the 4.0 or above standard for problems. Both of the values indicate no multicollinearity

Table 4.37
Correlations and Descriptive Statistics

Variables	AerCap (DV)	Grade	BodFat	PctMale	PctSES	PctMinority	PM10ATT
AerCap (DV)		-0.186**	0.391**	-0.112**	-0.319**	-0.265**	-0.098**
Grade			-0.046**	0.074**	-0.122**	-0.048**	-0.029**
BodFat				-0.100**	-0.491**	-0.428**	-0.127**
PctMale					0.020**	-0.002	-0.014*
PctSES						0.698**	0.231**
PctMinority							0.277**
PM10ATT							
Mean	59.54	6.07	67.45	51.44	52.45	67.70	0.58
S.D.	22.15	1.49	13.23	7.54	29.70	27.70	0.494

***p <0.05 ** p<0.01**

Three regression models were evaluated in this analysis. The first model was between Aerobic Capacity and PM_{10} Attainment status to determine if there was a significant relationship between these two variables. Because Aerobic Capacity may be influenced by several variables, a second model was run to evaluate the relationship between Aerobic Capacity and the independent variables Grade, BodFat, PctMale, PctSES and PctMinority. The third model investigated whether a relationship between Aerobic Capacity and PM_{10} Attainment Status existed after controlling for the variables in the second model.

Durbin-Watson was used to test for intercorrelation in the models. This value is 1.541 for the single independent variable model, and 1.716 for the multivariable models. These values are within the range of 1.0 to 3.0 so no intercorrelation exists.

Model 1

For the first model, a standard regression was conducted to determine the relationship between Aerobic Capacity and PM_{10} Attainment Status. Alpha was set at 0.05. The results indicate ($F(1, 16855) = 165$, $p<0.001$) that PM_{10} Attainment status is significantly related to Aerobic Capacity.

Table 4.38
Model 1: Standard Regression of PM10ATT for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
PM10ATT	**-4.416****	**-0.098**	**0.010**	**0.098**	**0.010**	**0.010**
	Intercept = 62.09					

***p <0.05 ** p<0.01**

As the regression coefficients in Table 4.38 indicate, PM_{10} Attainment status contributed significantly to Aerobic Capacity. The multiple correlation (R=0.098) indicated a very weak positive relationship between PM_{10} Attainment Status and Aerobic Capacity. Overall, the model (R^2=0.010) explained 1% of the variation in Aerobic Capacity.

Model 2

For the second model, a standard regression was conducted to determine the relationship between Aerobic Capacity and several non-environmental variables (Grade, BodFat, PctMale, PctSES, PctMinority) that may influence this endpoint. Alpha was set at 0.05. The results indicate ($F(5, 16851) = 931$, $p<0.001$) that at least one of the variables is significantly related to Aerobic Capacity.

Table 4.39
Model 2: Standard Regression of Variables for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	**-2.863****	**-0.193**	**0.0357**	**0.465**	**0.217**	**0.216**
Body Fat	**0.454****	**0.271**	**0.0534**			
Pct Male	**-0.196****	**-0.067**	**0.0044**			
Pct SES	**-0.141****	**-0.189**	**0.0164**			
Pct Minority	**-0.021****	**-0.026**	**0.0003**			
	Intercept = 65.19					

***p <0.05 ** p<0.01**

As the regression coefficients in Table 4.39 indicate, all variables contributed significantly to Aerobic Capacity. Beta weights indicate that Body Fat (β=0.271) was the strongest unique predictor, followed by Grade (β=-0.193), PctSES (β=-0.189), PctMale (β=-0.067) and PctMinority (β=-0.026). When only the unique variance explained by each variable is examined, Body Fat (sr^2=0.053) also accounts for the most variance in Aerobic Capacity, 5.3%, followed by Grade (sr^2=0.036) with 3.6%, PctSES (sr^2=0.016) with 1.6%, PctMale (sr^2=0.004) with 0.4%, and PctMinority (sr^2=0.0003) with 0.03%. Total unique variance was 11%. The zero-order correlations for BodFat, PctMale, PctSES and PctMinority were higher than their semipartial correlations, indicating shared variation with the other variables in the model. However, for Grade, the zero-order correlation was slightly lower than the corresponding semipartial correlation, indicating the possible presence of a suppressor variable. The semipartial correlation for PctMinority approaches zero, indicating the possible presence of a spurious or intervening relationship.

The multiple correlation (R=0.465) indicated a moderate positive relationship between the combination of independent variables and Aerobic Capacity. Overall, the model (R^2=0.217) explained 21.7% of the variation in Aerobic Capacity.

Model 3

For the third model, a standard regression was conducted to determine the relationship between Aerobic Capacity and PM_{10} Attainment Status after controlling for the independent variables in Model 2 (Grade, BodFat, PctMale, PctSES, PctMinority). Alpha was set at 0.05. The results indicate (F(6, 16850) = 778, p<0.001) that at least one of the variables is significantly related to Aerobic Capacity.

Table 4.40
Model 3: Standard Regression of Variables (incl. PM10ATT) for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	-2.866**	-0.193	0.0357	0.466	0.217	0.217
Body Fat	0.455**	0.271	0.0534			
Pct Male	-0.197**	-0.067	0.0045			
Pct SES	-0.140**	-0.188	0.0161			
Pct Minority	-0.017*	-0.021	0.0002			
PM10ATT	-0.961**	-0.021	0.0004			
	Intercept = 65.47					

***p <0.05 ** p<0.01**

As the regression coefficients in Table 4.40 indicate, all variables contributed significantly to Aerobic Capacity. Beta weights indicate that Body Fat (β=0.271) was the strongest unique predictor, followed by Grade (β=-0.193), PctSES (β=-0.188), PctMale (β=-0.067), PM_{10} Attainment Status (β=-0.021), and PctMinority (β=-0.021). When only the unique variance explained by each variable is examined, Body Fat (sr^2=0.053) also accounts for the most variance in Aerobic Capacity, 5.3%, followed by Grade (sr^2=0.036) with 3.6%, PctSES (sr^2=0.016) with 1.6%, PctMale (sr^2=0.005) with 0.5%, PM_{10} Attainment Status (sr^2=0.0004) with 0.04%, and PctMinority (sr^2=0.0002) with 0.02%. The zero-order correlations for BodFat, PctMale, PctSES, PctMinority and PM_{10} Attainment were higher than their semipartial correlations, indicating shared variation with the other variables in the model. However, for Grade, the zero-order correlation was slightly lower than the corresponding semipartial correlation, indicating the possible presence of a suppressor variable. The semipartial correlation for PctMinority approaches zero, indicating the possible presence of a spurious or intervening relationship.

The multiple correlation (R=0.466) indicated a moderate positive relationship between the combination of independent variables and Aerobic Capacity. Overall, the model (R^2=0.217) explained 21.7% of the variation in Aerobic Capacity.

The R^2 change between model 2 and model 3 was < 0.0005, indicating that the inclusion of PM_{10} Attainment status in the model added < 0.05% to the explanation of the variance in the model.

4.3.1.3 $PM_{2.5}$

Prior to the analysis, the independent variables (Grade, BodFat, PctMale, PctSES, PctMinority and PM2.5ATT) and the dependent variable Aerobic Capacity (AerCap) were screened for accuracy. First, the data were screened for missing values. PctSES was determined to be missing 2.4% of its data, since the percent of free/reduced price meals was unavailable for all schools. Because the percentage of missing data was less than 5%, Listwise deletion was used. No other variables were found to have missing data. All variables were determined to have values within their allowable ranges.

The data were next screened for influential outliers in solution. The maximum for Cook's distance was 0.004, well below the standard of 1.0 for problems. The minimum and maximum Studentized Deleted Residuals were -3.891 and 3.570, indicating that some values are outside the standard of $\pm$3.3. There are 16 values below -3.3 and 3 values greater than 3.3. Therefore, a scatterplot was generated to examine the outliers. The cases were examined to determine why they were outliers in solution. No pattern was detected with the outliers, so they were deleted from further analyses.

The Unstandardized residuals were screened for normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms indicated a unimodal, normal distribution with minimal skew. The Q-Q plot also showed little skew. Descriptive statistics were generated with the skewness of -0.385 for within the benchmark levels of $\pm$1.0. The kurtosis of -0.071 was within the kurtosis benchmark of $\pm$2.0. Thus, the assumption of a normal distribution was satisfied and no further transformations were required.

A scatterplot of standardized residuals against standardized predicted values was used to evaluate both linearity and homoscedasticity. Overall, the data were linear and evenly distributed, satisfying the assumptions of both linearity and homoscedasticity.

A correlation matrix (Table 4.41) was generated and all of the independent variables were significantly correlated ($p<0.001$) with the dependent variable. All of the correlations between IV's are less than 0.70, indicating no multicollinearity. To further explore multicollinearity, measures of tolerance and VIF were evaluated. Tolerance is 0.456 or higher for all variables, so it is well above the 0.20 standard for problems. The highest VIF is 2.194, well below the 4.0 or above standard for problems. Both of the values indicate no multicollinearity

Three regression models were evaluated in this analysis. The first model was between Aerobic Capacity and $PM_{2.5}$ Attainment status to determine if there was a significant relationship between these two variables. Because Aerobic Capacity may be influenced by several variables, a second model was run to evaluate the relationship between Aerobic Capacity and the independent variables Grade, BodFat, PctMale, PctSES and PctMinority. The third model investigated whether a relationship between Aerobic Capacity and $PM_{2.5}$ Attainment Status existed after controlling for the variables in the second model.

Table 4.41
Correlations and Descriptive Statistics

Variables	AerCap (DV)	Grade	BodFat	PctMale	PctSES	Pct Minority	PM2.5 ATT
AerCap (DV)		-0.186**	0.391**	-0.112**	-0.319**	-0.265**	-0.090**
Grade			-0.046**	0.074**	-0.122**	-0.047**	-0.026**
BodFat				-0.100**	-0.491**	-0.428**	-0.126**
PctMale					0.020**	-0.002	-0.013
PctSES						0.698**	0.236**
PctMinority							0.300**
PM2.5ATT							
Mean	59.55	6.07	67.45	51.44	52.45	67.70	0.54
S.D.	22.14	1.49	13.23	7.54	29.70	27.70	0.499

*p <0.05 ** p<0.01

Durbin-Watson was used to test for intercorrelation in the models. This value is 1.538 for the single independent variable model, and 1.715 for the multivariable models. These values are within the range of 1.0 to 3.0 so no intercorrelation exists.

<u>Model 1</u>

For the first model, a standard regression was conducted to determine the relationship between Aerobic Capacity and $PM_{2.5}$ Attainment Status. Alpha was set at 0.05. The results indicate ($F(1, 16854) = 136$, $p<0.001$) that $PM_{2.5}$ Attainment status is significantly related to Aerobic Capacity.

As the regression coefficients in Table 4.42 indicate, $PM_{2.5}$ Attainment status contributed significantly to Aerobic Capacity. The multiple correlation ($R=0.090$) indicated a very weak positive relationship between $PM_{2.5}$ Attainment Status and Aerobic Capacity. Overall, the model ($R^2=0.008$) explained 0.8% of the variation in Aerobic Capacity.

Table 4.42
Model 1: Standard Regression of PM2.5ATT for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
PM2.5ATT	-3.975**	-0.090	0.008	0.090	0.008	0.008
	Intercept = 61.68					

*p <0.05 ** p<0.01

Model 2

For the second model, a standard regression was conducted to determine the relationship between Aerobic Capacity and several non-environmental variables (Grade, BodFat, PctMale, PctSES, PctMinority) that may influence this endpoint. Alpha was set at 0.05. The results indicate ($F(5, 16850) = 932$, $p<0.001$) that at least one of the variables is significantly related to Aerobic Capacity.

Table 4.43
Model 2: Standard Regression of Variables for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	-2.865**	-0.193	0.0357	0.465	0.217	0.216
Body Fat	0.454**	0.271	0.0534			
Pct Male	-0.197**	-0.067	0.0045			
Pct SES	-0.141**	-0.189	0.0164			
Pct Minority	-0.021**	-0.026	0.0003			
	Intercept = 65.24					

*p <0.05 ** p<0.01

As the regression coefficients in Table 4.43 indicate, all variables contributed significantly to Aerobic Capacity. Beta weights indicate that Body Fat (β=0.271) was the strongest unique predictor, followed by Grade (β=-0.193), PctSES (β=-0.189), PctMale (β=-0.067) and PctMinority (β=-0.026). When only the unique variance explained by each variable is examined, Body Fat (sr^2=0.053) also accounts for the most variance in Aerobic Capacity, 5.3%, followed by Grade (sr^2=0.036) with 3.6%, PctSES (sr^2=0.016) with 1.6%, PctMale (sr^2=0.005) with 0.5%, and PctMinority (sr^2=0.0003) with 0.03%. Total unique variance was 11%. The zero-order correlations for BodFat, PctMale, PctSES and PctMinority were higher than their semipartial correlations, indicating shared variation with the other variables in the model. However, for Grade, the zero-order correlation was slightly lower than the corresponding semipartial correlation, indicating the possible presence of a suppressor variable. The semipartial correlation for PctMinority approaches zero, indicating the possible presence of a spurious or intervening relationship.

The multiple correlation (R=0.465) indicated a moderate positive relationship between the combination of independent variables and Aerobic Capacity. Overall, the model (R^2=0.217) explained 21.7% of the variation in Aerobic Capacity.

Model 3

For the third model, a standard regression was conducted to determine the relationship between Aerobic Capacity and $PM_{2.5}$ Attainment Status after controlling for the independent variables in Model 2 (Grade, BodFat, PctMale, PctSES, PctMinority). Alpha was set at 0.05. Based on evaluation of the regression coefficients in this model (Table 4.44), the addition of $PM_{2.5}$ Attainment status was found to be non-significant (p=0.182), indicating that this variable did not contribute any additional explanation of the variance of Aerobic Capacity.

Table 4.44
Model 3: Standard Regression of Variables (incl. PM2.5ATT) for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	-2.866**	-0.193	0.0357	0.466	0.217	0.216
Body Fat	0.455**	0.272	0.0538			
Pct Male	-0.197**	-0.067	0.0045			
Pct SES	-0.141**	-0.189	0.0161			
Pct Minority	-0.019*	-0.023	0.0003			
PM2.5ATT	-0.424	-0.010	0.0001			
	Intercept = 65.32					

***p <0.05 ** p<0.01**

4.3.2 Body Fat

4.3.2.1 Carbon Monoxide

Prior to the analysis, the independent variables (Grade, PctMale, PctSES, PctMinority and COATT) and the dependent variable Body Fat (BodFat) were screened for accuracy. First, the data were screened for missing values. PctSES was determined to be missing 2.4% of its data, since the percent of free/reduced price meals was unavailable for all schools. Because the percentage of missing data was less than 5%, Listwise deletion was used. No other variables were found to have missing data. All variables were determined to have values within their allowable ranges.

The maximum for Cook's distance is 0.013, well below the standard of 1.0 for problems. The minimum and maximum Studentized Deleted Residuals are -7.369 and 4.258. This indicates that some values are outside the standard of $\pm$3.3. There are 204 values below -3.3 and 17 values greater than 3.3. Therefore, we generated a scatterplot to examine the outliers using the values for Studentized Deleted Residuals and Standardized Values. The cases were examined to determine why they were outliers in solution. No consistent pattern was detected with the outliers, so they were deleted from further analyses.

The Unstandardized residuals were screened for normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms indicated a unimodal, normal distribution with minimal skew. The Q-Q plot also showed little skew. Descriptive statistics were generated with the skewness of -0.239 for within the benchmark levels of $\pm$1.0. The kurtosis of 1.566 was within the kurtosis benchmark of $\pm$2.0. Thus, the assumption of a normal distribution was satisfied and no further transformations were required.

A scatterplot of standardized residuals against standardized predicted values was used to evaluate both linearity and homoscedasticity. Overall, the data were linear and evenly distributed, satisfying the assumptions of both linearity and homoscedasticity.

A correlation matrix (Table 4.45) was generated and all of the independent variables were significantly correlated ($p<0.001$) with the dependent variable. The correlation between PctSES and PctMinority was 0.700, which was equal to the standard of 0.7 for multicollinearity. Upon review, the variable PctMinority was removed from the model. PctSES had a higher correlation with Body Fat and was therefore retained for further analysis. To further explore multicollinearity, measures of tolerance and VIF were evaluated. Tolerance is 0.978 or higher for all variables, so it is well above the 0.20 standard for problems. The highest VIF is 1.022, well below the 4.0 or above standard for problems. Both of the values indicate no multicollinearity

Table 4.45
Correlations and Descriptive Statistics

Variables	BodFat (DV)	Grade	PctMale	PctSES	COATT
BodFat (DV)		**-0..34****	**-0.110****	**-0.581****	**-0.059****
Grade			**0.072****	**-0.123****	**-0.032***
PctMale				**0.018***	**-0.005**
PctSES					**0.081****
COATT					
Mean	**68.13**	**6.07**	**51.41**	**52.48**	**0.19**
S.D.	**11.58**	**1.49**	**7.42**	**29.69**	**0.394**

***p <0.05 ** p<0.01**

Three regression models were evaluated in this analysis. The first model was between Body Fat and COATT to determine if there was a significant relationship between these two variables. Because Body Fat may be influenced by several variables, a second model was run to evaluate the relationship between Body Fat and the independent variables Grade, PctMale, and PctSES. The third model investigated whether a relationship between Body Fat and COATT existed after controlling for the variables in the second model.

Durbin-Watson was used to test for intercorrelation in the models. This value is 1.395 for the single independent variable model, and 1.718 for the multivariable models. These values are within the range of 1.0 to 3.0 so no intercorrelation exists.

Model 1

For the first model, a standard regression was conducted to determine the relationship between Body Fat and COATT. Alpha was set at 0.05. The results indicate ($F(1, 16652) = 59$, $p=<0.001$) that COATT is significantly related to Body Fat.

Table 4.46
Model 1: Standard Regression of COATT for Body Fat

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
COATT	**-1.744****	**-0.59**	**0.004**	**0.059**	**0.004**	**0.003**
	Intercept = 68.47					

$*p < 0.05$ ** $p<0.01$

As the regression coefficients in Table 4.46 indicate, COATT contributed significantly to Body Fat. The multiple correlation (R=0.059) indicated a very weak positive relationship between COATT and Body Fat. Overall, the model (R^2=0.004) explained 0.4% of the variation in Body Fat.

Model 2

For the second model, a standard regression was conducted to determine the relationship between Body Fat and several non-environmental variables (Grade, PctMale, PctSES) that may influence this endpoint. Alpha was set at 0.05. The results indicate ($F(3, 16650) = 3078$, $p<0.001$) that at least one of the variables is significantly related to Body Fat.

Table 4.47
Model 2: Standard Regression of Variables for Body Fat

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	-0.779**	-0.100	0.0098	0.597	0.357	0.357
Pct Male	-0.144**	-0.092	0.0085			
Pct SES	-0.231**	-0.591	0.3446			
	Intercept = 92.36					

*p <0.05 ** p<0.01

As the regression coefficients in Table 4.47 indicate, all variables contributed significantly to Body Fat. Beta weights indicate PctSES (β=-0.591) was the strongest unique predictor followed by Grade (β=-0.100), and PctMale (β=-0.092). When only the unique variance explained by each variable is examined, PctSES (sr^2=0.345) also accounts for the most variance in Body Fat, 34.5%, followed by Grade (sr^2=0.01) with 1%, and PctMale (sr^2=0.009) with 0.9%. Total unique variance was 36.3%. The semipartial correlation for PctMale in the second model is less than its zero-order correlation, indicating shared variance between the variables. The semipartial correlations for PctSES and Grade are slightly larger than their zero-order correlations, indicating the presence of a suppressor variable.

The multiple correlation (R=0.597) indicated a moderate positive relationship between the combination of independent variables and Body Fat. Overall, the model (R^2=0.357) explained 35.7% of the variation in Body Fat.

Model 3

For the third model, a standard regression was conducted to determine the relationship between Body Fat and COATT after controlling for the independent variables in Model 2 (Grade, PctMale, PctSES). Alpha was set at 0.05. The results indicate ($F(4, 16649) = 2310$, $p<0.001$) that at least one of the variables is significantly related to Body Fat.

Table 4.48
Model 3: Standard Regression of Variables (including COATT) for Body Fat

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	-0.782**	-0.100	0.0098	0.597	0.357	0.357
Pct Male	-0.144**	-0.092	0.0085			
Pct SES	-0.230**	-0.590	0.3411			
COATT	-0.457*	-0.016	0.0003			
	Intercept = 92.44					

*p <0.05 ** p<0.01

As the regression coefficients in Table 4.48 indicate, all variables contributed significantly to Body Fat. Beta weights indicate that PctSES (β= -0.590) was the strongest unique predictor, followed by Grade (β=-0.100), PctMale (β=-0.092), and COATT (β=-0.016). When only the unique variance explained by each variable is examined, PctSES (sr^2=0.341) also accounts for the most variance in Body Fat, 34.1%, followed by Grade (sr^2=0.01) with 1%, PctMale (sr^2=0.009) with 0.9%, and COATT (sr^2=0.0003) with 0.03%. Total unique variance was 36%. The semipartial correlations for PctMale and COATT in the third model are less than their zero-order correlations, indicating shared variance between the variables. The semipartial correlations for Grade and PctSES are slightly larger than their zero-order correlations, indicating the presence of a suppressor variable.

The multiple correlation (R=0.597) indicated a moderate positive relationship between the combination of independent variables and Body Fat. Overall, the model (R^2=0.357) explained 35.7% of the variation in Body Fat.

The R^2 change between model 2 and model 3 was <0.0005, indicating that the inclusion of COATT in the model added <0.05% to the explanation of the variance in the model.

4.3.2.2 8-hour Ozone

Prior to the analysis, the independent variables (Grade, PctMale, PctSES, PctMinority and O3ATT) and the dependent variable Body Fat (BodFat) were screened for accuracy. First, the data were screened for missing values. PctSES was determined to be missing 2.4% of its data, since the percent of free/reduced price meals was unavailable for all schools. Because the percentage of missing data was less than 5%, Listwise deletion was used. No other variables were found to have missing data. All variables were determined to have values within their allowable ranges.

The maximum for Cook's distance is 0.012, well below the standard of 1.0 for problems. The minimum and maximum Studentized Deleted Residuals are -7.388 and 4.248. This indicates that some values are outside the standard of ±3.3. There are 205 values below -3.3 and 17 values greater than 3.3. Therefore, we generated a scatterplot to examine the outliers using the values for Studentized Deleted Residuals and Standardized Values. The cases were examined to determine why they were outliers in solution. No consistent pattern was detected with the outliers, so they were deleted from further analyses.

The Unstandardized residuals were screened for normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms indicated a unimodal, normal distribution with minimal skew. The Q-Q plot also showed little skew. Descriptive statistics were generated with the skewness of -0.230 for within the benchmark levels of ±1.0. The kurtosis of 1.558 was within the kurtosis benchmark of ±2.0. Thus, the assumption of a normal distribution was satisfied and no further transformations were required.

A scatterplot of standardized residuals against standardized predicted values was used to evaluate both linearity and homoscedasticity. Overall, the data were linear and evenly distributed, satisfying the assumptions of both linearity and homoscedasticity.

Table 4.49
Correlations and Descriptive Statistics

Variables	BodFat (DV)	Grade	PctMale	PctSES	O3ATT
BodFat (DV)		-0..34**	-0.109**	-0.581**	-0.016*
Grade			0.072**	-0.123**	-0.052*
PctMale				0.018*	-0.008
PctSES					0.007
O3ATT					
Mean	68.13	6.07	51.41	52.49	0.91
S.D.	11.58	1.49	7.43	29.69	0.287

***p <0.05 ** p<0.01**

A correlation matrix (Table 4.49) was generated and all of the independent variables were significantly correlated ($p<0.05$) with the dependent variable. The correlation between PctSES and PctMinority was 0.700, which was equal to the standard of 0.7 for multicollinearity. Upon review, the variable PctMinority was removed from the model. PctSES had a higher correlation with Body Fat and was therefore retained for further analysis. To further explore multicollinearity, measures of tolerance and VIF were evaluated. Tolerance is 0.977 or higher for all variables, so it is well above the 0.20 standard for problems. The highest VIF is 1.024, well below the 4.0 or above standard for problems. Both of the values indicate no multicollinearity

Three regression models were evaluated in this analysis. The first model was between Body Fat and O3ATT to determine if there was a significant relationship between these two variables. Because Body Fat may be influenced by several variables, a second model was run to evaluate the relationship between Body Fat and the independent variables Grade, PctMale, and PctSES. The third model investigated whether a relationship between Body Fat and O3ATT existed after controlling for the variables in the second model.

Durbin-Watson was used to test for intercorrelation in the models. This value is 1.390 for the single independent variable model, and 1.719 for the multivariable models. These values are within the range of 1.0 to 3.0 so no intercorrelation exists.

Model 1

For the first model, a standard regression was conducted to determine the relationship between Body Fat and O3ATT. Alpha was set at 0.05. The results indicate ($F(1, 16651) = 4.06$, $p=0.044$) that O3ATT is significantly related to Body Fat.

Table 4.50
Model 1: Standard Regression of O3ATT for Body Fat

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
O3ATT	**-0.630***	**-0.016**	**0.0003**	**0.016**	**0.000**	**0.000**
	Intercept = 68.70					

***p <0.05 ** p<0.01**

As the regression coefficients in Table 4.50 indicate, O3ATT contributed significantly to Body Fat. The multiple correlation (R=0.016) indicated a very weak positive relationship between O3ATT and Body Fat. Overall, the model (R^2=<0.0005) explained <0.05% of the variation in Body Fat.

Model 2

For the second model, a standard regression was conducted to determine the relationship between Body Fat and several non-environmental variables (Grade, PctMale, PctSES) that may influence this endpoint. Alpha was set at 0.05. The results indicate ($F(3, 16649) = 3080$, $p<0.001$) that at least one of the variables is significantly related to Body Fat.

Table 4.51
Model 2: Standard Regression of Variables for Body Fat

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	-0.781**	-0.100	0.0098	0.597	0.357	0.357
Pct Male	-0.142**	-0.091	0.0083			
Pct SES	-0.231**	-0.591	0.3446			
	Intercept = 92.29					

*p <0.05 ** p<0.01

As the regression coefficients in Table 4.51 indicate, all variables contributed significantly to Body Fat. Beta weights indicate PctSES (β=-0.591) was the strongest unique predictor followed by Grade (β=-0.100), and PctMale (β=-0.091). When only the unique variance explained by each variable is examined, PctSES (sr^2=0.345) also accounts for the most variance in Body Fat, 34.5%, followed by Grade (sr^2=0.01) with 1%, and PctMale (sr^2=0.008) with 0.8%. Total unique variance was 36.3%. The semipartial correlation for PctMale in the second model is less than its zero-order correlation, indicating shared variance between the variables. The semipartial correlations for PctSES and Grade are slightly larger than their zero-order correlations, indicating the presence of a suppressor variable.

The multiple correlation (R=0.597) indicated a moderate positive relationship between the combination of independent variables and Body Fat. Overall, the model (R^2=0.357) explained 35.7% of the variation in Body Fat.

<u>Model 3</u>

For the third model, a standard regression was conducted to determine the relationship between Body Fat and O3ATT after controlling for the independent variables in Model 2 (Grade, PctMale, PctSES). Alpha was set at 0.05. The results indicate ($F(4, 16648) = 2313$, $p<0.001$) that at least one of the variables is significantly related to Body Fat.

Table 4.52
Model 3: Standard Regression of Variables (including O3ATT) for Body Fat

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	-0.788**	-0.101	0.0100	0.598	0.357	0.357
Pct Male	-0.142**	-0.091	0.0083			
Pct SES	-0.231**	-0.591	0.3446			
O3ATT	-0.714**	-0.018	0.0003			
	Intercept = 92.99					

***p <0.05 ** p<0.01**

As the regression coefficients in Table 4.52 indicate, all variables contributed significantly to Body Fat. Beta weights indicate that PctSES (β= -0.591) was the strongest unique predictor, followed by Grade (β=-0.101), PctMale (β=-0.091), and O3ATT (β=-0.018). When only the unique variance explained by each variable is examined, PctSES (sr^2=0.345) also accounts for the most variance in Body Fat, 34.5%, followed by Grade (sr^2=0.01) with 1%, PctMale (sr^2=0.008) with 0.8%, and O3ATT (sr^2=0.0003) with 0.03%. Total unique variance was 36.3%. The semipartial correlation for PctMale in the third model is less than its zero-order correlation, indicating shared variance between the variables. The semipartial correlations for Grade, PctSES, and O3ATT are slightly larger than their zero-order correlations, indicating the presence of a suppressor variable. The multiple correlation (R=0.597) indicated a moderate positive relationship between the combination of independent variables and Body Fat. Overall, the model (R^2=0.357) explained 35.7% of the variation in Body Fat.

The R^2 change between model 2 and model 3 was <0.0005, indicating that the inclusion of O3ATT in the model added <0.05% to the explanation of the variance in the model.

4.3.2.3 PM_{10}

Prior to the analysis, the independent variables (Grade, PctMale, PctSES, PctMinority and PM10ATT) and the dependent variable Body Fat (BodFat) were screened for accuracy. First, the data were screened for missing values. PctSES was determined to be missing 2.4% of its data, since the percent of free/reduced price meals was unavailable for all schools. Because the percentage of missing data was less than 5%, Listwise deletion was used. No other variables were found to have missing data. All variables were determined to have values within their allowable ranges.

The maximum for Cook's distance is 0.011, well below the standard of 1.0 for problems. The minimum and maximum Studentized Deleted Residuals are -7.367 and 4.252. This indicates that some values are outside the standard of $\pm$3.3. There are 204 values below -3.3 and 17 values greater than 3.3. Therefore, we generated a scatterplot to examine the outliers using the values for Studentized Deleted Residuals and Standardized Values. The cases were examined to determine why they were outliers in solution. No consistent pattern was detected with the outliers, so they were deleted from further analyses.

The Unstandardized residuals were screened for normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms indicated a unimodal, normal distribution with minimal skew. The Q-Q plot also showed little skew. Descriptive statistics were generated with the skewness of -0.243 for within the benchmark levels of $\pm$1.0. The kurtosis of 1.567 was within the kurtosis benchmark of $\pm$2.0. Thus, the assumption of a normal distribution was satisfied and no further transformations were required.

A scatterplot of standardized residuals against standardized predicted values was used to evaluate both linearity and homoscedasticity. Overall, the data were linear and evenly distributed, satisfying the assumptions of both linearity and homoscedasticity.

A correlation matrix (Table 4.53) was generated and all of the independent variables were significantly correlated ($p<0.001$) with the dependent variable. The correlation between PctSES and PctMinority was 0.700, which was equal to the standard of 0.7 for multicollinearity. Upon review, the variable PctMinority was removed from the model. PctSES had a higher correlation with Body Fat and was therefore retained for further analysis. To further explore multicollinearity, measures of tolerance and VIF were evaluated. Tolerance is 0.932 or higher for all variables, so it is well above the 0.20 standard for problems. The highest VIF is 1.072, well below the 4.0 or above standard for problems. Both of the values indicate no multicollinearity

Table 4.53
Correlations and Descriptive Statistics

Variables	BodFat (DV)	Grade	PctMale	PctSES	PM10ATT
BodFat (DV)		-0.034**	-0.110**	-0.581**	-0.162**
Grade			0.072**	-0.123**	-0.029**
PctMale				0.018*	-0.014*
PctSES					0.231**
PM10ATT					
Mean	68.13	6.07	51.41	52.48	0.58
S.D.	11.58	1.49	7.42	29.69	0.494

*p <0.05 ** p<0.01

Three regression models were evaluated in this analysis. The first model was between Body Fat and PM10ATT to determine if there was a significant relationship between these two variables. Because Body Fat may be influenced by several variables, a second model was run to evaluate the relationship between Body Fat and the independent variables Grade, PctMale, and PctSES. The third model investigated whether a relationship between Body Fat and PM10ATT existed after controlling for the variables in the second model.

Durbin-Watson was used to test for intercorrelation in the models. This value is 1.427 for the single independent variable model, and 1.718 for the multivariable models. These values are within the range of 1.0 to 3.0 so no intercorrelation exists.

Model 1

For the first model, a standard regression was conducted to determine the relationship between Body Fat and PM10ATT. Alpha was set at 0.05. The results indicate ($F(1, 16652) = 447$, $p=<0.001$) that PM10ATT is significantly related to Body Fat.

Table 4.54
Model 1: Standard Regression of PM10ATT for Body Fat

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
PM10ATT	**-3.792****	**-0.162**	**0.026**	**0.162**	**0.026**	**0.026**
	Intercept = 70.33					

***p <0.05 ** p<0.01**

As the regression coefficients in Table 4.54 indicate, PM10ATT contributed significantly to Body Fat. The multiple correlation ($R=0.162$) indicated a very weak positive relationship between PM10ATT and Body Fat. Overall, the model ($R^2=0.026$) explained 2.6% of the variation in Body Fat.

Model 2

For the second model, a standard regression was conducted to determine the relationship between Body Fat and several non-environmental variables (Grade, PctMale, PctSES) that may influence this endpoint. Alpha was set at 0.05. The results indicate ($F(3, 16650) = 3078$, $p<0.001$) that at least one of the variables is significantly related to Body Fat.

As the regression coefficients in Table 4.55 indicate, all variables contributed significantly to Body Fat. Beta weights indicate PctSES ($\beta=-0.591$) was the strongest unique predictor followed by Grade ($\beta=-0.100$), and PctMale ($\beta=-0.092$). When only the unique variance explained by each variable is examined, PctSES (sr^2=0.345) also accounts for the most variance in Body Fat, 34.5%, followed by Grade (sr^2=0.01) with 1%, and PctMale (sr^2=0.009) with 0.9%. Total unique variance was 36.3%. The semipartial correlation for PctMale in the second model is less than its zero-order correlation, indicating shared variance between the variables. The semipartial correlations for PctSES and Grade are slightly larger than their zero-order correlations, indicating the presence of a suppressor variable.

Table 4.55
Model 2: Standard Regression of Variables for Body Fat

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	-0.779**	-0.100	0.0098	0.597	0.357	0.357
Pct Male	-0.144**	-0.092	0.0085			
Pct SES	-0.231**	-0.591	0.3446			
	Intercept = 92.36					

***p <0.05 ** p<0.01**

The multiple correlation (R=0.597) indicated a moderate positive relationship between the combination of independent variables and Body Fat. Overall, the model (R^2=0.357) explained 35.7% of the variation in Body Fat.

<u>Model 3</u>

For the third model, a standard regression was conducted to determine the relationship between Body Fat and PM10ATT after controlling for the independent variables in Model 2 (Grade, PctMale, PctSES). Alpha was set at 0.05. The results indicate ($F(4, 16649) = 2317$, $p<0.001$) that at least one of the variables is significantly related to Body Fat.

As the regression coefficients in Table 4.56 indicate, all variables contributed significantly to Body Fat. Beta weights indicate that PctSES (β= -0.584) was the strongest unique predictor, followed by Grade (β=-0.100), PctMale (β=-0.093), and PM10ATT (β=-0.031). When only the unique variance explained by each variable is examined, PctSES (sr^2=0.318) also accounts for the most variance in Body Fat, 31.8%, followed by Grade (sr^2=0.01) with 1%, PctMale (sr^2=0.009) with 0.9%, and PM10ATT (sr^2=0.00093) with 0.09%. Total unique variance was 33.7%. The semipartial correlations for PctMale, PctSES, and PM10ATT in the third model are less than their zero-order correlations, indicating shared variance between the variables. The semipartial correlation for Grade is slightly larger than its zero-order correlation, indicating the presence of a suppressor variable.

Table 4.56
Model 3: Standard Regression of Variables (including PM10ATT) for Body Fat

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	-0.779**	-0.100	0.0098	0.598	0.358	0.357
Pct Male	-0.145**	-0.092	0.0085			
Pct SES	-0.228**	-0.590	0.3181			
PM10ATT	-0.731*	-0.016	0.0009			
	Intercept = 92.68					

***p <0.05 ** p<0.01**

The multiple correlation (R=0.598) indicated a moderate positive relationship between the combination of independent variables and Body Fat. Overall, the model (R^2=0.358) explained 35.8% of the variation in Body Fat.

The R^2 change between model 2 and model 3 was 0.001, indicating that the inclusion of PM10ATT in the model added 0.1% to the explanation of the variance in the model.

4.3.2.3 $PM_{2.5}$

Prior to the analysis, the independent variables (Grade, PctMale, PctSES, PctMinority and PM2.5ATT) and the dependent variable Body Fat (BodFat) were screened for accuracy. First, the data were screened for missing values. PctSES was determined to be missing 2.4% of its data, since the percent of free/reduced price meals was unavailable for all schools. Because the percentage of missing data was less than 5%, Listwise deletion was used. No other variables were found to have missing data. All variables were determined to have values within their allowable ranges.

The maximum for Cook's distance is 0.012, well below the standard of 1.0 for problems. The minimum and maximum Studentized Deleted Residuals are -7.364 and 4.246. This indicates that some values are outside the standard of $\pm$3.3. There are 203 values below -3.3 and 18 values greater than 3.3. Therefore, we generated a scatterplot to examine the outliers using the values for Studentized Deleted Residuals and Standardized Values. The cases were examined to determine why they were outliers in solution. No consistent pattern was detected with the outliers, so they were deleted from further analyses.

The Unstandardized residuals were screened for normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms indicated a unimodal, normal distribution with minimal skew. The Q-Q plot also showed little skew. Descriptive statistics were generated with the skewness of -0.248 for within the benchmark levels of $\pm$1.0. The kurtosis of 1.568 was within the kurtosis benchmark of $\pm$2.0. Thus, the assumption of a normal distribution was satisfied and no further transformations were required.

A scatterplot of standardized residuals against standardized predicted values was used to evaluate both linearity and homoscedasticity. Overall, the data were linear and evenly distributed, satisfying the assumptions of both linearity and homoscedasticity.

A correlation matrix (Table 4.57 was generated and all of the independent variables were significantly correlated ($p<0.001$) with the dependent variable. The correlation between PctSES and PctMinority was 0.700, which was equal to the standard of 0.7 for multicollinearity. Upon review, the variable PctMinority was removed from the model. PctSES had a higher correlation with Body Fat and was therefore retained for further analysis. To further explore multicollinearity, measures of tolerance and VIF were evaluated. Tolerance is 0.930 or higher for all variables, so it is well above the 0.20 standard for problems. The highest VIF is 1.075, well below the 4.0 or above standard for problems. Both of the values indicate no multicollinearity.

Table 4.57
Correlations and Descriptive Statistics

Variables	BodFat (DV)	Grade	PctMale	PctSES	PM2.5ATT
BodFat (DV)		-0.034**	-0.110**	-0.581**	-0.165**
Grade			0.072**	-0.123**	-0.026**
PctMale				0.018*	-0.011
PctSES					0.236**
PM2.5ATT					
Mean	68.13	6.07	51.41	52.48	0.54
S.D.	11.58	1.49	7.42	29.69	0.499

*p <0.05 ** p<0.01

Three regression models were evaluated in this analysis. The first model was between Body Fat and PM2.5ATT to determine if there was a significant relationship between these two variables. Because Body Fat may be influenced by several variables, a second model was run to evaluate the relationship between Body Fat and the independent variables Grade, PctMale, and PctSES. The third model investigated whether a relationship between Body Fat and PM2.5ATT existed after controlling for the variables in the second model.

Durbin-Watson was used to test for intercorrelation in the models. This value is 1.428 for the single independent variable model, and 1.719 for the multivariable models. These values are within the range of 1.0 to 3.0 so no intercorrelation exists.

Model 1

For the first model, a standard regression was conducted to determine the relationship between Body Fat and PM2.5ATT. Alpha was set at 0.05. The results indicate ($F(1, 16652) = 463$, $p=<0.001$) that PM2.5ATT is significantly related to Body Fat.

Table 4.58
Model 1: Standard Regression of PM2.5ATT for Body Fat

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
PM2.5ATT	**-3.822****	**-0.165**	**0.027**	**0.165**	**0.027**	**0.027**
	Intercept = 70.19					

***p <0.05 ** p<0.01**

As the regression coefficients in Table 4.58 indicate, PM2.5ATT contributed significantly to Body Fat. The multiple correlation ($R=0.165$) indicated a very weak positive relationship between PM2.5ATT and Body Fat. Overall, the model ($R^2=0.027$) explained 2.7% of the variation in Body Fat.

Model 2

For the second model, a standard regression was conducted to determine the relationship between Body Fat and several non-environmental variables (Grade, PctMale, PctSES) that may influence this endpoint. Alpha was set at 0.05. The results indicate ($F(3, 16650) = 3077$, $p<0.001$) that at least one of the variables is significantly related to Body Fat.

As the regression coefficients in Table 4.59 indicate, all variables contributed significantly to Body Fat. Beta weights indicate PctSES ($\beta=-0.591$) was the strongest unique predictor followed by Grade ($\beta=-0.100$), and PctMale ($\beta=-0.092$). When only the unique variance explained by each variable is examined, PctSES ($sr^2=0.343$) also accounts for the most variance in Body Fat, 34.3%, followed by Grade ($sr^2=0.01$) with 1%, and PctMale ($sr^2=0.009$) with 0.9%. Total unique variance was 36.2%. The semipartial correlation for PctMale in the second model is less than its zero-order correlation, indicating shared variance between the variables. The semipartial correlations for PctSES and Grade are slightly larger than their zero-order correlations, indicating the presence of a suppressor variable.

Table 4.59
Model 2: Standard Regression of Variables for Body Fat

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	-0.777**	-0.100	0.0098	0.597	0.357	0.357
Pct Male	-0.144**	-0.092	0.0085			
Pct SES	-0.231**	-0.591	0.3434			
	Intercept = 92.34					

*p <0.05 ** p<0.01

The multiple correlation (R=0.597) indicated a moderate positive relationship between the combination of independent variables and Body Fat. Overall, the model (R^2=0.357) explained 35.7% of the variation in Body Fat.

<u>Model 3</u>

For the third model, a standard regression was conducted to determine the relationship between Body Fat and PM2.5ATT after controlling for the independent variables in Model 2 (Grade, PctMale, PctSES). Alpha was set at 0.05. The results indicate ($F(4, 16649) = 2316$, $p<0.001$) that at least one of the variables is significantly related to Body Fat.

As the regression coefficients in Table 4.60 indicate, all variables contributed significantly to Body Fat. Beta weights indicate that PctSES (β= -0.584) was the strongest unique predictor, followed by Grade (β=-0.100), PctMale (β=-0.093), and PM2.5ATT (β=-0.030). When only the unique variance explained by each variable is examined, PctSES (sr^2=0.317) also accounts for the most variance in Body Fat, 31.71%, followed by Grade (sr^2=0.01) with 1%, PctMale (sr^2=0.009) with

0.9%, and PM2.5ATT (sr^2=0.0008) with 0.08%. Total unique variance was 33.6%. The semipartial correlations for PctMale, PctSES, and PM2.5ATT in the third model are less than their zero-order correlations, indicating shared variance between the variables. The semipartial correlation for Grade is slightly larger than its zero-order correlation, indicating the presence of a suppressor variable.

Table 4.60
Model 3: Standard Regression of Variables (including PM2.5ATT) for Body Fat

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	**-0.776****	**-0.100**	**0.0098**	**0.598**	**0.358**	**0.357**
Pct Male	**-0.145****	**-0.093**	**0.0085**			
Pct SES	**-0.228****	**-0.584**	**0.3170**			
PM2.5ATT	**-0.704****	**-0.030**	**0.0008**			
	Intercept = 92.6					

***p <0.05 ** p<0.01**

The multiple correlation (R=0.598) indicated a moderate positive relationship between the combination of independent variables and Body Fat. Overall, the model (R^2=0.358) explained 35.8% of the variation in Body Fat.

The R^2 change between model 2 and model 3 was 0.001, indicating that the inclusion of PM2.5ATT in the model added 0.1% to the explanation of the variance in the model.

4.4 Specific Aim 4

For those criteria pollutants for which an association with aerobic capacity exists after adjustment for demographic factors, determine if there is a dose-response type relationship within counties with non-attainment status.

As shown in Section 4.3.1.3, after adjustment for demographic factors the addition of $PM_{2.5}$ Attainment status did not offer any additional explanatory power to the regression model. Therefore, $PM_{2.5}$ was not carried through to Specific Aim 4. Attainment status for Carbon Monoxide, 8-hour Ozone, and PM_{10} were all significant after controlling for demographic factors. Because, Carbon Monoxide had insufficient data for further evaluation (see Section 3.2.5), only 8-hour Ozone and PM_{10} were evaluated further. Because we know that Aerobic Capacity pass rates at a school are lower in the non-attainment area, the focus was to further investigate the data within the non-attainment areas to determine if a dose-response type relationship existed. This was done through a series of multiple regression analyses as summarized below.

An additional assessment (Section 4.4.4) was performed to see if Aerobic Capacity passing rates were associated with a variable known as the Air Quality Index (AQI) that reflects the overall air quality within a county. For this assessment, the number of times the Air Quality Index exceeded a value of 100 for all counties within California during the year preceding fitness testing was associated with Aerobic Capacity passing rates.

4.4.1 Exceedances of Air Quality Standards

4.4.1.1 8-Hour Ozone

Prior to the analysis, the independent variables (Grade, BodFat, PctMale, PctSES, and PreO3Exceed) and the dependent variable Aerobic Capacity (AerCap) were screened for accuracy. First, the data were screened for missing values. PctSES was determined to be missing 2.3% of its data, since the percent of free/reduced price meals was unavailable for all schools. Because the percentage of missing data was less than 5%, Listwise deletion was used. No other variables were found to have missing data. All variables were determined to have values within their allowable ranges.

The maximum for Cook's distance is 0.006, well below the standard of 1.0 for problems. The minimum and maximum Studentized Deleted Residuals are -3.856 and 3.563. This indicates that some values are outside the standard of $\pm$3.3. There are 16 values below -3.3 and 3 values greater than 3.3. Therefore, we generated a scatterplot to examine the outliers using the values for Studentized Deleted Residuals and Standardized Values. The cases were examined to determine why they were outliers in solution. No pattern was detected with the outliers, so they were deleted from further analyses.

The Unstandardized residuals were screened for normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms indicated a unimodal, normal distribution with minimal skew. The Q-Q plot also showed little skew. Descriptive statistics were generated with the skewness of -0.381 for within the benchmark levels of +1.0. The kurtosis of -0.069 was within the kurtosis benchmark of +2.0. Thus, the assumption of a normal distribution was satisfied and no further transformations were required.

A scatterplot of standardized residuals against standardized predicted values was used to evaluate both linearity and homoscedasticity. Overall, the data were linear and evenly distributed, satisfying the assumptions of both linearity and homoscedasticity.

A correlation matrix (Table 4.61) was generated and all of the independent variables were significantly correlated ($p<0.001$) with the dependent variable. The correlations between the independent variables were all less than the standard of 0.7, indicating no problems with multicollinearity. To further explore multicollinearity, measures of tolerance and VIF were evaluated. Tolerance is 0.684 or higher for all variables, so it is well above the 0.20 standard for problems. The highest VIF is 1.462, well below the 4.0 or above standard for problems. Both of the values indicate no multicollinearity

Table 4.61
Correlations and Descriptive Statistics

Variables	AerCap (DV)	Grade	BodFat	PctMale	PctSES	PreO3Exceed
AerCap (DV)		-0.194**	0.399**	-0.116**	-0.327**	-0.118**
Grade			-0.056**	0.073**	-0.116**	-0.003
BodFat				-0.098**	-0.502**	-0.125**
PctMale					0.014*	-0.013*
PctSES						0.269**
PreO3Exceed						
Mean	59.38	6.05	67.40	51.42	52.53	51.26
S.D.	22.23	1.48	13.20	7.34	30.09	39.46

*p <0.05 ** p<0.01

Three regression models were evaluated in this analysis. The first model was between Aerobic Capacity and PreO3Exceed to determine if there was a significant relationship between these two variables. Because Aerobic Capacity may be influenced by several variables, a second model was run to evaluate the relationship between Aerobic Capacity and the independent variables Grade, BodFat, PctMale, and PctSES. The third model investigated whether a relationship between Aerobic Capacity and PreO3Exceed existed after controlling for the variables in the second model.

Durbin-Watson was used to test for intercorrelation in the models. This value is 1.521 for the single independent variable model, and 1.701 for the multivariable models. These values are within the range of 1.0 to 3.0 so no intercorrelation exists.

<u>Model 1</u>

For the first model, a standard regression was conducted to determine the relationship between Aerobic Capacity and PreO3Exceed. Alpha was set at 0.05. The results indicate ($F(1, 15316) = 218$, $p=0.001$) that PreO3Exceed is significantly related to Aerobic Capacity.

Table 4.62
Model 1: Standard Regression of PreO3Exceed for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
PreO3Exceed	-0.067**	-0.118	0.014	0.118	0.014	0.014
	Intercept = 62.80					

*p <0.05 ** p<0.01

As the regression coefficients in Table 4.62 indicate, PreO3Exceed contributed significantly to Aerobic Capacity. The multiple correlation (R=0.118) indicated a very weak positive relationship between PreO3Exceed and Aerobic Capacity. Overall, the model (R^2=0.014) explained 1.4% of the variation in Aerobic Capacity.

Model 2

For the second model, a standard regression was conducted to determine the relationship between Aerobic Capacity and several non-environmental variables (Grade, BodFat, PctMale, PctSES) that may influence this endpoint. Alpha was set at 0.05. The results indicate (F(4, 15313) = 1112, p<0.001) that at least one of the variables is significantly related to Aerobic Capacity.

Table 4.63
Model 2: Standard Regression of Variables for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	-2.968**	-0.198	0.0376	0.474	0.225	0.225
BodFat	0.462**	0.274	0.0548			
Pct Male	-0.217**	-0.072	0.0050			
Pct SES	-0.156**	-0.211	0.0324			
	Intercept = 65.53					

*p <0.05 ** p<0.01

As the regression coefficients in Table 4.63 indicate, all variables contributed significantly to Aerobic Capacity. Beta weights indicate that Body Fat (β=0.234) was the strongest unique predictor, followed by Grade (β=-0.194), PctSES (β=-0.18), and PctMale (β=-0.071). When only the unique variance explained by each variable is examined, Body Fat (sr^2=0.055) also accounts for the most variance in Aerobic Capacity, 5.5%, followed by Grade (sr^2=0.038) with 3.8%, PctSES (sr^2=0.032) with 3.2%, and PctMale (sr^2=0.005) with 0.5%. Total unique variance was 13%. The semipartial correlations for BodyFat, PctMale and Pct SES in the second model are less than their zero-order correlations, indicating shared variance between the variables. The semipartial correlation for Grade is the same as its zero-order correlation.

The multiple correlation (R=0.474) indicated a moderate positive relationship between the combination of independent variables and Aerobic Capacity. Overall, the model (R^2=0.225) explained 22.5% of the variation in Aerobic Capacity.

<u>Model 3</u>

For the third model, a standard regression was conducted to determine the relationship between Aerobic Capacity and PreO3Exceed after controlling for the independent variables in Model 2 (Grade, BodFat, PctMale, PctSES). Alpha was set at 0.05. The results indicate ($F(5, 15312) = 894$, $p<0.001$) that at least one of the variables is significantly related to Aerobic Capacity.

Table 4.64
Model 3: Standard Regression of Variables (including PreO3Exceed) for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	-2.953**	-0.197	0.0372	0.475	0.226	0.226
BodFat	0.463**	0.275	0.0548			
Pct Male	-0.218**	-0.072	0.0052			
Pct SES	-0.149**	-0.202	0.0279			
PreO3Exceed	-0.018**	-0.031	0.0009			
	Intercept = 66.04					

***p <0.05 ** p<0.01**

As the regression coefficients in Table 4.64 indicate, all variables contributed significantly to Aerobic Capacity. Beta weights indicate that Body Fat (β=0.234) was the strongest unique predictor, followed by Grade (β=-0.193), PctSES (β=-0.167), PctMale (β=-0.072), and PreO3Exceed (β=-0.03). When only the unique variance explained by each variable is examined, Body Fat (sr^2=0.055) also accounts for the most variance in Aerobic Capacity, 5.5%, followed by Grade (sr^2=0.037) with 3.7%, PctSES (sr^2=0.028) with 2.8%, PctMale (sr^2=0.005) with 0.5%, and PreO3Exceed (sr^2=0.001) with 0.1%. Total unique variance was 12.6%. The semipartial correlations for Grade, BodFat, PctMale, Pct SES, and PreO3Exceed in the third model are less than their zero-order correlations, indicating shared variance between the variables.

The multiple correlation (R=0.475) indicated a moderate positive relationship between the combination of independent variables and Aerobic Capacity. Overall, the model (R^2=0.226) explained 22.6% of the variation in Aerobic Capacity.

The R^2 change between model 2 and model 3 was 0.001, indicating that the inclusion of PreO3Exceed in the model added 0.1% to the explanation of the variance in the model.

4.4.1.2 PM_{10}

Prior to the analysis, the independent variables (Grade, BodFat, PctMale, PctSES, and PrePM10Exceed) and the dependent variable Aerobic Capacity (AerCap) were screened for accuracy. First, the data were screened for missing values. PctSES was determined to be missing 1.8% of its data, since the percent of free/reduced price meals was unavailable for all schools. PrePM10Exceed was missing a total of 1.1% of its data due to lack of measurements. Because the percentage of missing data was less than 5%, Listwise deletion was used. No other variables were found to have missing data. All variables were determined to have values within their allowable ranges.

The maximum for Cook's distance is 0.007, well below the standard of 1.0 for problems. The minimum and maximum Studentized Deleted Residuals are -3.794 and 3.010. This indicates that some values are outside the standard of +3.3. There are 14 values below -3.3 and 0 values greater than 3.3. Therefore, we generated a scatterplot to examine the outliers using the values for Studentized Deleted Residuals and Standardized Values. The cases were examined to determine why they were outliers in solution. No pattern was detected with the outliers, so they were deleted from further analyses.

The Unstandardized residuals were screened for normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms indicated a unimodal, normal distribution with minimal skew. The Q-Q plot also showed little skew. Descriptive statistics were generated with the skewness of -0.330 for within the benchmark levels of +1.0. The kurtosis of -0.189 was within the kurtosis benchmark of +2.0. Thus, the assumption of a normal distribution was satisfied and no further transformations were required.

A scatterplot of standardized residuals against standardized predicted values was used to evaluate both linearity and homoscedasticity. Overall, the data were linear and evenly distributed, satisfying the assumptions of both linearity and homoscedasticity.

Table 4.65
Correlations and Descriptive Statistics

Variables	AerCap (DV)	Grade	BodFat	PctMale	PctSES	PrePM10 Exceed
AerCap (DV)		-0.194**	0.364**	-0.111**	-0.287**	-0.036**
Grade			-0.049**	0.058**	-0.122**	0.024**
BodFat				-0.100**	-0.504**	-0.041**
PctMale					0.006	-0.003
PctSES						0.061**
PrePM10Exceed						
Mean	57.67	6.03	66.04	51.33	58.33	69.15
S.D.	21.97	1.47	12.41	7.20	29.42	68.69

*p <0.05 ** p<0.01

A correlation matrix (Table 4.65) was generated and all of the independent variables were significantly correlated ($p<0.001$) with the dependent variable. The correlations between the independent variables were all less than the standard of 0.7, indicating no problems with multicollinearity. To further explore multicollinearity, measures of tolerance and VIF were evaluated. Tolerance is 0.721 or higher for all variables, so it is well above the 0.20 standard for problems. The highest VIF is 1.387, well below the 4.0 or above standard for problems. Both of the values indicate no multicollinearity

Three regression models were evaluated in this analysis. The first model was between Aerobic Capacity and PrePM10Exceed to determine if there was a significant relationship between these two variables. Because Aerobic Capacity may be influenced by several variables, a second model was run to evaluate the relationship between Aerobic Capacity and the independent variables Grade, BodFat, PctMale, and PctSES. The third model investigated whether a relationship between Aerobic Capacity and PrePM10Exceed existed after controlling for the variables in the second model.

Durbin-Watson was used to test for intercorrelation in the models. This value is 1.523 for the single independent variable model, and 1.697 for the multivariable models. These values are within the range of 1.0 to 3.0 so no intercorrelation exists.

Model 1

For the first model, a standard regression was conducted to determine the relationship between Aerobic Capacity and PrePM10Exceed. Alpha was set at 0.05. The results indicate ($F(1, 9618) = 12.1$, $p=0.001$) that PrePM10Exceed is significantly related to Aerobic Capacity.

Table 4.66
Model 1: Standard Regression of PrePM10Exceed for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
PrePM10Exceed	-0.011**	-0.036	0.001	0.036	0.001	0.001
	Intercept = 58.46					

*p <0.05 ** p<0.01

As the regression coefficients in Table 4.66 indicate, PrePM10Exceed contributed significantly to Aerobic Capacity. The multiple correlation (R=0.036) indicated a very weak positive relationship between PrePM10Exceed and Aerobic Capacity. Overall, the model (R^2=0.001) explained 0.1% of the variation in Aerobic Capacity.

Model 2

For the second model, a standard regression was conducted to determine the relationship between Aerobic Capacity and several non-environmental variables (Grade, BodFat, PctMale, PctSES) that may influence this endpoint. Alpha was set at 0.05. The results indicate (F(4, 9615) = 572, p<0.001) that at least one of the variables is significantly related to Aerobic Capacity.

Table 4.67
Model 2: Standard Regression of Variables for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	-2.983**	-0.200	0.0388	0.438	0.192	0.192
BodFat	0.450**	0.254	0.0471			
Pct Male	-0.223**	-0.073	0.0052			
Pct SES	-0.137**	-0.183	0.0243			
	Intercept = 65.33					

*p <0.05 ** p<0.01

As the regression coefficients in Table 4.67 indicate, all variables contributed significantly to Aerobic Capacity. Beta weights indicate that Body Fat (β=0.254) was the strongest unique predictor, followed by Grade (β=-0.200), PctSES (β=-0.183), and PctMale (β=-0.073). When only the unique variance explained by each variable is examined, Body Fat (sr^2=0.047) also accounts for the most variance in Aerobic Capacity, 4.7%, followed by Grade (sr^2=0.039) with 3.9%, PctSES (sr^2=0.0242) with 2.4%, and PctMale (sr^2=0.005) with 0.5%. Total unique variance was 11.58%. The zero-order correlations for BodFat, PctMale and PctSES were higher than their semipartial correlations, indicating shared variation with the other variables in the model. However, for Grade, the zero-order correlation was slightly lower than the corresponding semipartial correlation, indicating the possible presence of a suppressor variable.

The multiple correlation (R=0.438) indicated a moderate positive relationship between the combination of independent variables and Aerobic Capacity. Overall, the model (R^2=0.19.2) explained 19.2% of the variation in Aerobic Capacity.

<u>Model 3</u>

For the third model (Table 4.68), a standard regression was conducted to determine the relationship between Aerobic Capacity and PM10Exceed after controlling for the independent variables in Model 2 (Grade, BodFat, PctMale, PctSES). Alpha was set at 0.05. Based on evaluation of the regression coefficients in this model, the addition of PM10Exceed was found to be non-significant (p=0.308), indicating that this variable did not contribute any additional explanation of the variance of Aerobic Capacity.

Table 4.68
Model 3: Standard Regression of Variables (incl. PrePM10Exceed) for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	-2.978**	-0.200	0.0384	0.439	0192	0.192
BodFat	0.450**	0.254	0.0471			
Pct Male	-0.223**	-0.073	0.0052			
Pct SES	-0.136**	-0.183	0.0240			
PrePM10Exceed	-0.003	-0.009	0.0001			
	Intercept = 65.50					

***p <0.05 ** p<0.01**

4.4.2 Number of Person Days Exceeding Air Quality Standards

4.4.2.1 8-Hour Ozone

Prior to the analysis, the independent variables (Grade, BodFat, PctMale, PctSES, and PreO3PersDays) and the dependent variable Aerobic Capacity (AerCap) were screened for accuracy. First, the data were screened for missing values. PctSES was determined to be missing 2.3% of its data, since the percent of free/reduced price meals was unavailable for all schools. Because the percentage of missing data was less than 5%, Listwise deletion was used. No other variables were found to have missing data. All variables were determined to have values within their allowable ranges.

The data were next screened for influential outliers in solution. The maximum for Cook's distance was 0.006, well below the standard of 1.0 for problems. The minimum and maximum Studentized Deleted Residuals were -3.860 and 3.624, indicating that some values are outside the standard of $\pm$3.3. There are 12 values below -3.3 and 3 values greater than +3.3. Therefore, a scatterplot was generated to examine the outliers. The cases were examined to determine why they were outliers in solution. No pattern was detected with the outliers, so they were deleted from further analyses.

The Unstandardized residuals were screened for normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms indicated a unimodal, normal distribution with minimal skew. The Q-Q plot also showed little skew. Descriptive statistics were generated with the skewness of -0.384 for within the benchmark levels of +1.0. The kurtosis of -0.061 was within the kurtosis benchmark of +2.0. Thus, the assumption of a normal distribution was satisfied and no further transformations were required.

A scatterplot of standardized residuals against standardized predicted values was used to evaluate both linearity and homoscedasticity. Overall, the data were linear and evenly distributed, satisfying the assumptions of both linearity and homoscedasticity.

A correlation matrix (Table 4.69) was generated and all of the independent variables were significantly correlated ($p<0.001$) with the dependent variable. All of the correlations between IV's are less than 0.70, indicating no multicollinearity. To further explore multicollinearity, measures of tolerance and VIF were evaluated. Tolerance is 0.698 or higher for all variables, so it is well above the 0.20 standard for problems. The highest VIF is 1.433, well below the 4.0 or above standard for problems. Both of the values indicate no multicollinearity

Table 4.69
Correlations and Descriptive Statistics

Variables	AerCap (DV)	Grade	BodFat	PctMale	PctSES	PreO3 PersDays
AerCap (DV)		-0.193**	0.398**	-0.116**	-0.326**	-0.067**
Grade			-0.056**	0.073**	-0.116**	-0.016*
BodFat				-0.098**	-0.502**	-0.116**
PctMale					0.014*	-0.015*
PctSES						0.230**
PreO3PersDays						
Mean	59.36	6.05	67.40	51.42	52.52	245.15
S.D.	22.24	1.48	13.20	7.34	30.09	334.88

***p <0.05 ** p<0.01**

Three regression models were evaluated in this analysis. The first model was between Aerobic Capacity and PreO3PersDays to determine if there was a significant relationship between these two variables. Because Aerobic Capacity may be influenced by several variables, a second model was run to evaluate the relationship between Aerobic Capacity and the independent variables Grade, BodFat, PctMale, and PctSES. The third model investigated whether a relationship between Aerobic Capacity and PreO3PersDays existed after controlling for the variables in the second model.

Durbin-Watson was used to test for intercorrelation in the models. This value is 1.509 for the single independent variable model, and 1.702 for the multivariable models. These values are within the range of 1.0 to 3.0 so no intercorrelation exists.

Model 1

For the first model, a standard regression was conducted to determine the relationship between Aerobic Capacity and PreO3PersDays. Alpha was set at 0.05. The results indicate ($F(1, 15320) = 68.33$, $p<0.001$) that PreO3PersDays is significantly related to Aerobic Capacity.

Table 4.70
Model 1: Standard Regression of PreO3PersDays for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
PreO3PersDays	-0.004**	-0.067	0.004	0.067	0.004	0.004
	Intercept = 60.45					

*p <0.05 ** p<0.01

As the regression coefficients in Table 4.70 indicate, PreO3PersDays contributed significantly to Aerobic Capacity. The multiple correlation (R=0.067) indicated a very weak positive relationship between PreO3PersDays and Aerobic Capacity. Overall, the model (R^2=0.004) explained 0.4% of the variation in Aerobic Capacity.

Model 2

For the second model, a standard regression was conducted to determine the relationship between Aerobic Capacity and several non-environmental variables (Grade, BodFat, PctMale, PctSES) that may influence this endpoint. Alpha was set at 0.05. The results indicate (F(5, 15317) = 1106, p<0.001) that at least one of the variables is significantly related to Aerobic Capacity.

Table 4.71
Model 2: Standard Regression of Variables for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	-2.959**	-0.197	0.0376	0.473	0.224	0.224
BodFat	0.462**	0.274	0.0548			
Pct Male	-0.217**	-0.072	0.0050			
Pct SES	-0.156**	-0.210	0.0320			
	Intercept = 65.46					

***p <0.05 ** p<0.01**

As the regression coefficients in Table 4.71 indicate, all variables contributed significantly to Aerobic Capacity. Beta weights indicate that Body Fat (β=0.274) was the strongest unique predictor, followed by PctSES (β=-0.210), Grade (β=-0.197), and PctMale (β=-0.072). When only the unique variance explained by each variable is examined, Body Fat (sr^2=0.055) also accounts for the most variance in Aerobic Capacity, 5.5%, followed by Grade (sr^2=0.038) with 3.8%, PctSES (sr^2=0.032) with 3.2%, and PctMale (sr^2=0.005) with 0.5%. Total unique variance was 13%. The zero-order correlations for BodFat, PctMale, and PctSES were higher than their semipartial correlations, indicating shared variation with the other variables in the model.

However, for Grade, the zero-order correlation was slightly lower than the corresponding semipartial correlation, indicating the possible presence of a suppressor variable.

The multiple correlation (R=0.473) indicated a moderate positive relationship between the combination of independent variables and Aerobic Capacity. Overall, the model (R^2=0.224) explained 22.4% of the variation in Aerobic Capacity.

<u>Model 3</u>

For the third model (Table 4.72), a standard regression was conducted to determine the relationship between Aerobic Capacity and PreO3PersDays after controlling for the independent variables in Model 2 (Grade, BodFat, PctMale, PctSES). Alpha was set at 0.05.

Table 4.72
Model 3: Standard Regression of Variables (incl. PreO3PersDays) for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	-2.961**	-0.197	0.0376	0.473	0.224	0.224
BodFat	0.462**	0.274	0.0548			
Pct Male	-0.216**	-0.071	0.0050			
Pct SES	-0.157**	-0.213	0.0317			
PreO3PersDays	-0.001	-0.010	0.0001			
	Intercept = 65.37					

***p <0.05 ** p<0.01**

Based on evaluation of the regression coefficients in this model, the addition of PreO3PersDays was found to be non-significant (p=0.174), indicating that this variable did not contribute any additional explanation of the variance of Aerobic Capacity.

4.4.2.2 PM_{10}

Prior to the analysis, the independent variables (Grade, BodFat, PctMale, PctSES, and PrePM10PersDays) and the dependent variable Aerobic Capacity (AerCap) were screened for accuracy. First, the data were screened for missing values. PctSES was determined to be missing 1.8% of its data, since the percent of free/reduced price meals was unavailable for all schools. PrePM10PersDays was missing a total of 1.1% of its data due to lack of measurements. Because the percentage of missing data was less than 5%, Listwise deletion was used. No other variables were found to have missing data. All variables were determined to have values within their allowable ranges.

The maximum for Cook's distance is 0.007, well below the standard of 1.0 for problems. The minimum and maximum Studentized Deleted Residuals are -3.808 and 3.027. This indicates that some values are outside the standard of +3.3. There are 6 values below -3.3 and 0 values greater than +3.3. Therefore, we generated a scatterplot to examine the outliers using the values for Studentized Deleted Residuals and Standardized Values. The cases were examined to determine why they were outliers in solution. No pattern was detected with the outliers, so they were deleted from further analyses.

The Unstandardized residuals were screened for normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms indicated a unimodal, normal distribution with minimal skew. The Q-Q plot also showed little skew. Descriptive statistics were generated with the skewness of -0.331 for within the benchmark levels of +1.0. The kurtosis of -0.185 was within the kurtosis benchmark of +2.0. Thus, the assumption of a normal distribution was satisfied and no further transformations were required.

A scatterplot of standardized residuals against standardized predicted values was used to evaluate both linearity and homoscedasticity. Overall, the data were linear and evenly distributed, satisfying the assumptions of both linearity and homoscedasticity.

Table 4.73
Correlations and Descriptive Statistics

Variables	AerCap (DV)	Grade	BodFat	PctMale	PctSES	PrePM10 PersDays
AerCap (DV)		-0.194**	0.364**	-0.111**	-0.287**	-0.004
Grade			-0.049**	0.058**	-0.122**	-0.016
BodFat				-0.100**	-0.504**	-0.038**
PctMale					0.007	-0.013
PctSES						0.109**
PrePM10PersDays						
Mean	57.66	6.03	66.04	51.33	58.32	205.56
S.D.	21.97	1.47	12.41	7.20	29.42	152.84

*p <0.05 ** p<0.01

A correlation matrix (Table 4.73) was generated and all of the independent variables, with the exception of PrePM10PersDays were significantly correlated ($p<0.001$) with the dependent variable. Because PrePM10PersDays was not significantly correlated ($p=0.364$) with Aerobic Capacity, no further analyses were performed.

4.4.3 Annual Average Concentrations

4.4.3.1 8-Hour Ozone

Prior to the analysis, the independent variables (Grade, BodFat, PctMale, PctSES, and PreO3AnnAvg) and the dependent variable Aerobic Capacity (AerCap) were screened for accuracy. First, the data were screened for missing values. PctSES was determined to be missing 2.3% of its data, since the percent of free/reduced price meals was unavailable for all schools. Because the percentage of missing data was less than 5%, Listwise deletion was used. No other variables were found to have missing data. All variables were determined to have values within their allowable ranges.

The maximum for Cook's distance is 0.006, well below the standard of 1.0 for problems. The minimum and maximum Studentized Deleted Residuals are -3.856 and 3.525. This indicates that some values are outside the standard of $\pm$3.3. There are 14 values below -3.3 and 3 values greater than 3.3. Therefore, we generated a scatterplot to examine the outliers using the values for Studentized Deleted Residuals and Standardized Values. The cases were examined to determine why they were outliers in solution. No pattern was detected with the outliers, so they were deleted from further analyses.

The Unstandardized residuals were screened for normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms indicated a unimodal, normal distribution with minimal skew. The Q-Q plot also showed little skew. Descriptive statistics were generated with the skewness of -0.385 for within the benchmark levels of +1.0. The kurtosis of -0.061 was within the kurtosis benchmark of +2.0. Thus, the assumption of a normal distribution was satisfied and no further transformations were required.

A scatterplot of standardized residuals against standardized predicted values was used to evaluate both linearity and homoscedasticity. Overall, the data were linear and evenly distributed, satisfying the assumptions of both linearity and homoscedasticity.

A correlation matrix (Table 4.74) was generated and all of the independent variables were significantly correlated ($p<0.001$) with the dependent variable. The correlations between the independent variables were all less than the standard of 0.7, indicating no problems with multicollinearity. To further explore multicollinearity, measures of tolerance and VIF were evaluated. Tolerance is 0.688 or higher for all variables, so it is well above the 0.20 standard for problems. The highest VIF is 1.452, well below the 4.0 or above standard for problems. Both of the values indicate no multicollinearity

Table 4.74
Correlations and Descriptive Statistics

Variables	AerCap (DV)	Grade	BodFat	PctMale	PctSES	PreO3 AnnAvg
AerCap (DV)		-0.194**	0.398**	-0.116**	-0.326**	-0.113**
Grade			-0.056**	0.073**	-0.116**	-0.003
BodFat				-0.098**	-0.502**	-0.117**
PctMale					0.014*	-0.012
PctSES						0.254**
PreO3AnnAvg						
Mean	59.37	6.05	67.40	51.42	52.52	0.063
S.D.	22.24	1.48	13.20	7.34	30.09	0.014

*p <0.05 ** p<0.01

Three regression models were evaluated in this analysis. The first model was between Aerobic Capacity and PreO3AnnAvg to determine if there was a significant relationship between these two variables. Because Aerobic Capacity may be influenced by several variables, a second model was run to evaluate the relationship between Aerobic Capacity and the independent variables Grade, BodFat, PctMale, and PctSES. The third model investigated whether a relationship between Aerobic Capacity and PreO3AnnAvg existed after controlling for the variables in the second model.

Durbin-Watson was used to test for intercorrelation in the models. This value is 1.520 for the single independent variable model, and 1.700 for the multivariable models. These values are within the range of 1.0 to 3.0 so no intercorrelation exists.

Model 1

For the first model, a standard regression was conducted to determine the relationship between Aerobic Capacity and PreO3AnnAvg. Alpha was set at 0.05. The results indicate ($F(1, 15318) = 199$, $p=0.001$) that PreO3AnnAvg is significantly related to Aerobic Capacity.

Table 4.75
Model 1: Standard Regression of PreO3AnnAvg for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
PreO3AnnAvg	**-183.38****	**-0.113**	**0.013**	**0.113**	**0.013**	**0.013**
	Intercept =70.85					

***p <0.05 ** p<0.01**

As the regression coefficients in Table 4.75 indicate, PreO3AnnAvg contributed significantly to Aerobic Capacity. The multiple correlation (R=0.113) indicated a very weak positive relationship between PreO3AnnAvg and Aerobic Capacity. Overall, the model (R^2=0.013) explained 1.3% of the variation in Aerobic Capacity.

Model 2

For the second model, a standard regression was conducted to determine the relationship between Aerobic Capacity and several non-environmental variables (Grade, BodFat, PctMale, PctSES) that may influence this endpoint. Alpha was set at 0.05. The results indicate (F(4, 15315) = 1108, p<0.001) that at least one of the variables is significantly related to Aerobic Capacity.

As the regression coefficients in Table 4.76 indicate, all variables contributed significantly to Aerobic Capacity. Beta weights indicate that Body Fat (β=0.234) was the strongest unique predictor, followed by Grade (β=-0.194), PctSES (β=-0.179), and PctMale (β=-0.071). When only the unique variance explained by each variable is examined, Body Fat (sr^2=0.055) also accounts for the most variance in Aerobic Capacity, 5.3%, followed by Grade (sr^2=0.038) with 3.8%, PctSES (sr^2=0.032) with 3.2%, and PctMale (sr^2=0.005) with 0.5%. Total unique variance was 13%. The zero-order correlations for Grade, BodFat, PctMale and PctSES were higher than their semipartial correlations, indicating shared variation with the other variables in the model.

Table 4.76
Model 2: Standard Regression of Variables for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	-2.963**	-0.197	0.0376	0.474	0.224	0.224
BodFat	0.462**	0.274	0.0548			
Pct Male	-0.216**	-0.071	0.0050			
Pct SES	-0.156**	-0.210	0.0320			
	Intercept = 65.41					

*p <0.05 ** p<0.01

The multiple correlation (R=0.474) indicated a moderate positive relationship between the combination of independent variables and Aerobic Capacity. Overall, the model (R^2=0.224) explained 22.4% of the variation in Aerobic Capacity.

Model 3

For the third model, a standard regression was conducted to determine the relationship between Aerobic Capacity and PreO3AnnAvg after controlling for the independent variables in Model 2 (Grade, BodFat, PctMale, PctSES). Alpha was set at 0.05. The results indicate ($F(5, 15314) = 891$, $p<0.001$) that at least one of the variables is significantly related to Aerobic Capacity.

As the regression coefficients in Table 4.77 indicate, all variables contributed significantly to Aerobic Capacity. Beta weights indicate that Body Fat (β=0.234) was the strongest unique predictor, followed by Grade (β=-0.193), PctSES (β=-0.168), PctMale (β=-0.071), and PreO3AnnAvg (β=-0.03). When only the unique variance explained by each variable is examined, Body Fat (sr^2=0.055) also accounts for the most variance in Aerobic Capacity, 5.5%, followed by Grade (sr^2=0.037) with 3.7%, PctSES (sr^2=0.028) with 2.8%, PctMale (sr^2=0.005) with 0.5%, and PreO3AnnAvg (sr^2=0.001) with 0.1%. Total unique variance was 12.6%. The zero-order correlations for Grade, BodFat, PctMale, PctSES, and PrePreO3AnnAvg were higher than their semipartial correlations, indicating shared variation with the other variables in the model.

Table 4.77
Model 3: Standard Regression of Variables (incl. PreO3AnnAvg) for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	-2.949**	-0.197	0.0372	0.475	0.225	0.225
BodFat	0.463**	0.275	0.0548			
Pct Male	-0.217**	-0.072	0.0050			
Pct SES	-0.149**	-0.202	0.0282			
PreO3AnnAvg	-50.38**	-0.031	0.0009			
	Intercept = 68.18					

*p <0.05 ** p<0.01

The multiple correlation (R=0.475) indicated a moderate positive relationship between the combination of independent variables and Aerobic Capacity. Overall, the model (R^2=0.225) explained 22.5% of the variation in Aerobic Capacity.

The R^2 change between model 2 and model 3 was 0.001, indicating that the inclusion of PreO3AnnAvg in the model added 0.1% to the explanation of the variance in the model.

4.4.3.2 PM_{10}

Prior to the analysis, the independent variables (Grade, BodFat, PctMale, PctSES, and PrePM10AnnAvg) and the dependent variable Aerobic Capacity (AerCap) were screened for accuracy. First, the data were screened for missing values. PctSES was determined to be missing 1.8% of its data, since the percent of free/reduced price meals was unavailable for all schools. PrePM10AnnAvg was missing a total of 1.1% of its data due to lack of measurements. Because the percentage of missing data was less than 5%, Listwise deletion was used. No other variables were found to have missing data. All variables were determined to have values within their allowable ranges.

The maximum for Cook's distance is 0.007, well below the standard of 1.0 for problems. The minimum and maximum Studentized Deleted Residuals are -3.789 and 3.014. This indicates that some values are outside the standard of +3.3. There are 7 values below -3.3 and 0 values greater than +3.3. Therefore, we generated a scatterplot to examine the outliers using the values for Studentized Deleted Residuals and Standardized Values. The cases were examined to determine why they were outliers in solution. No pattern was detected with the outliers, so they were deleted from further analyses.

The Unstandardized residuals were screened for normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms indicated a unimodal, normal distribution with minimal skew. The Q-Q plot also showed little skew. Descriptive statistics were generated with the skewness of -0.329 for within the benchmark levels of +1.0. The kurtosis of -0.190 was within the kurtosis benchmark of +2.0. Thus, the assumption of a normal distribution was satisfied and no further transformations were required.

A scatterplot of standardized residuals against standardized predicted values was used to evaluate both linearity and homoscedasticity. Overall, the data were linear and evenly distributed, satisfying the assumptions of both linearity and homoscedasticity.

A correlation matrix (Table 4.78) was generated and all of the independent variables were significantly correlated ($p<0.001$) with the dependent variable. The correlations between the independent variables were all less than the standard of 0.7, indicating no problems with multicollinearity. To further explore multicollinearity, measures of tolerance and VIF were evaluated. Tolerance is 0.709 or higher for all variables, so it is well above the 0.20 standard for problems. The highest VIF is 1.411, well below the 4.0 or above standard for problems. Both of the values indicate no multicollinearity

Table 4.78
Correlations and Descriptive Statistics

Variables	AerCap (DV)	Grade	BodFat	PctMale	PctSES	PrePM10 AnnAvg
AerCap (DV)		-0.194**	0.364**	-0.111**	-0.287**	-0.067**
Grade			-0.049**	0.058**	-0.122**	-0.036**
BodFat				-0.100**	-0.504**	-0.099**
PctMale					0.006	-0.008
PctSES						0.164**
PrePM10AnnAvg						
Mean	57.67	6.03	66.04	51.32	58.33	32.06
S.D.	21.97	1.47	12.41	7.20	29.41	5.82

$^*p <0.05$ ** $p<0.01$

Three regression models were evaluated in this analysis. The first model was between Aerobic Capacity and PrePM10AnnAvg to determine if there was a significant relationship between these two variables. Because Aerobic Capacity may be influenced by several variables, a second model was run to evaluate the relationship between Aerobic Capacity and the independent variables Grade, BodFat, PctMale, and PctSES. The third model investigated whether a relationship between Aerobic Capacity and PrePM10AnnAvg existed after controlling for the variables in the second model.

Durbin-Watson was used to test for intercorrelation in the models. This value is 1.527 for the single independent variable model, and 1.697 for the multivariable models. These values are within the range of 1.0 to 3.0 so no intercorrelation exists.

Model 1

For the first model, a standard regression was conducted to determine the relationship between Aerobic Capacity and PrePM10AnnAvg. Alpha was set at 0.05. The results indicate ($F(1, 9618) = 42.7$, $p=0.001$) that PrePM10AnnAvg is significantly related to Aerobic Capacity.

Table 4.79
Model 1: Standard Regression of PrePM10AnnAvg for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
PrePM10AnnAvg	**-0.251****	**-0.067**	**0.004**	**0.067**	**0.004**	**0.004**
	Intercept = 65.33					

***p <0.05 ** p<0.01**

As the regression coefficients in Table 4.79 indicate, PrePM10AnnAvg contributed significantly to Aerobic Capacity. The multiple correlation (R=0.067) indicated a very weak positive relationship between PrePM10AnnAvg and Aerobic Capacity. Overall, the model (R^2=0.004) explained 0.4% of the variation in Aerobic Capacity.

Model 2

For the second model, a standard regression was conducted to determine the relationship between Aerobic Capacity and several non-environmental variables (Grade, BodFat, PctMale, PctSES) that may influence this endpoint. Alpha was set at 0.05. The results indicate ($F(4, 9615) = 572$, $p<0.001$) that at least one of the variables is significantly related to Aerobic Capacity.

Table 4.80
Model 2: Standard Regression of Variables for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	**-2.983****	**-0.200**	**0.0388**	**0.438**	**0.192**	**0.192**
BodFat	**0.450****	**0.254**	**0.0471**			
Pct Male	**-0.223****	**-0.073**	**0.0052**			
Pct SES	**-0.137****	**-0.183**	**0.0243**			
	Intercept = 65.33					

***p <0.05 ** p<0.01**

As the regression coefficients in Table 4.80 indicate, all variables contributed significantly to Aerobic Capacity. Beta weights indicate that Body Fat (β=0.254) was the strongest unique predictor, followed by Grade (β=-0.200), PctSES (β=-0.183), and PctMale (β=-0.073). When only the unique variance explained by each variable is examined, Body Fat (sr^2=0.047) also accounts for the most variance in Aerobic Capacity, 4.7%, followed by Grade (sr^2=0.038) with 3.8%, PctSES (sr^2=0.024) with 2.4%, and PctMale (sr^2=0.005) with 0.5%. Total unique variance was 11.5%. The zero-order correlations for BodFat, PctMale and PctSES were higher than their semipartial correlations, indicating shared variation with the other variables in the model. However, for Grade, the zero-order correlation was slightly lower than the corresponding semipartial correlation, indicating the possible presence of a suppressor variable.

The multiple correlation (R=0.438) indicated a moderate positive relationship between the combination of independent variables and Aerobic Capacity. Overall, the model (R^2=0.192) explained 19.2% of the variation in Aerobic Capacity.

<u>Model 3</u>

For the third model (Table 4.81), a standard regression was conducted to determine the relationship between Aerobic Capacity and PM10AnnAvg after controlling for the independent variables in Model 2 (Grade, BodFat, PctMale, PctSES). Alpha was set at 0.05. Based on evaluation of the regression coefficients in this model, the addition of PM10AnnAvg was found to be non-significant (p=0.597), indicating that this variable did not contribute any additional explanation of the variance of Aerobic Capacity.

Table 4.81
Model 3: Standard Regression of Variables (incl. PrePM10AnnAvg) for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	-2.979**	-0.200	0.0384	0.438	0.192	0.192
BodFat	0.450**	0.254	0.0471			
Pct Male	-0.223**	-0.073	0.0052			
Pct SES	-0.136**	-0.182	0.0234			
PrePM10AnnAvg	-0.019	-0.005	0.0000			
	Intercept = 65.88					

***p <0.05 ** p<0.01**

4.4.4 Air Quality Index

Prior to the analysis, the independent variables (Grade, BodFat, PctMale, PctSES, and PreAQI) and the dependent variable Aerobic Capacity (AerCap) were screened for accuracy. First, the data were screened for missing values. PctSES was determined to be missing 2.4% of its data, since the percent of free/reduced price meals was unavailable for all schools. PreAQI was missing a total of 3.5% of its data because only those counties with 365 days of data were used in this analysis. Because the percentage of missing data was less than 5%, Listwise deletion was used. No other variables were found to have missing data. All variables were determined to have values within their allowable ranges.

The data were next screened for influential outliers in solution. The maximum for Cook's distance was 0.004, well below the standard of 1.0 for problems. The minimum and maximum Studentized Deleted Residuals were -3.878 and 3.528, indicating that some values are outside the standard of $\pm$3.3. There are 15 values below -3.3 and 3 values greater than 3.3. Therefore, a scatterplot was generated to examine the outliers. The cases were examined to determine why they were outliers in solution. No pattern was detected with the outliers, so they were deleted from further analyses.

The Unstandardized residuals were screened for normality using visual and statistical methods. First histograms and Q-Q Normal Probability Plots were examined. The histograms indicated a unimodal, normal distribution with minimal skew. The Q-Q plot also showed little skew. Descriptive statistics were generated with the skewness of -0.391 for within the benchmark levels of +1.0. The kurtosis of -0.059 was within the kurtosis benchmark of +2.0. Thus, the assumption of a normal distribution was satisfied and no further transformations were required.

A scatterplot of standardized residuals against standardized predicted values was used to evaluate both linearity and homoscedasticity. Overall, the data were linear and evenly distributed, satisfying the assumptions of both linearity and homoscedasticity.

Table 4.82
Correlations and Descriptive Statistics

Variables	AerCap (DV)	Grade	BodFat	PctMale	PctSES	PreAQI
AerCap (DV)		-0.187**	0.394**	-0.114**	-0.322**	-0.121**
Grade			-0.049**	0.077**	-0.121**	-0.014*
BodFat				-0.101**	-0.498**	-0.126**
PctMale					0.019**	-0.020**
PctSES						0.269**
PreAQI						
Mean	59.62	6.06	67.46	51.45	52.26	58.48
S.D.	22.21	1.49	13.23	7.46	29.95	46.14

*p <0.05 ** p<0.01

A correlation matrix (Table 4.82) was generated and all of the independent variables were significantly correlated ($p<0.001$) with the dependent variable. The correlation between the independent variables were all less than the standard of 0.7, indicating no problems with multicollinearity. To further explore multicollinearity, measures of tolerance and VIF were evaluated. Tolerance is 0.689 or higher for all variables, so it is well above the 0.20 standard for problems. The highest VIF is 1.452, well below the 4.0 or above standard for problems. Both of the values indicate no multicollinearity

Three regression models were evaluated in this analysis. The first model was between Aerobic Capacity and PreAQI to determine if there was a significant relationship between these two variables. Because Aerobic Capacity may be influenced by several variables, a second model was run to evaluate the relationship between Aerobic Capacity and the independent variables Grade, BodFat, PctMale, and PctSES. The third model investigated whether a relationship between Aerobic Capacity and PreAQI existed after controlling for the variables in the second model.

Durbin-Watson was used to test for intercorrelation in the models. This value is 1.537 for the single independent variable model, and 1.707 for the multivariable models. These values are within the range of 1.0 to 3.0 so no intercorrelation exists.

Model 1

For the first model, a standard regression was conducted to determine the relationship between Aerobic Capacity and PreAQI. Alpha was set at 0.05. The results indicate ($F(1, 16252) = 241$, $p<0.001$) that PreAQI is significantly related to Aerobic Capacity.

Table 4.83
Model 1: Standard Regression of PreAQI for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
PreAQI	-0.058**	-0.121	0.015	0.121	0.015	0.015
	Intercept = 63.02					

*p <0.05 ** p<0.01

As the regression coefficients in Table 4.83 indicate, PreAQI contributed significantly to Aerobic Capacity. The multiple correlation (R=0.121) indicated a very weak positive relationship between PreAQI and Aerobic Capacity. Overall, the model (R^2=0.015) explained 1.5% of the variation in Aerobic Capacity.

Model 2

For the second model, a standard regression was conducted to determine the relationship between Aerobic Capacity and several non-environmental variables (Grade, BodFat, PctMale, PctSES) that may influence this endpoint. Alpha was set at 0.05. The results indicate (F(4, 16249) = 1138, p<0.001) that at least one of the variables is significantly related to Aerobic Capacity.

Table 4.84
Model 2: Standard Regression of Variables for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	-2.891**	-0.193	0.0361	0.468	0.219	0.219
BodFat	0.462**	0.275	0.0552			
Pct Male	-0.200**	-0.067	0.0045			
Pct SES	-0.154**	-0.207	0.0313			
	Intercept = 64.32					

***p <0.05 ** p<0.01**

As the regression coefficients in Table 4.84 indicate, all variables contributed significantly to Aerobic Capacity. Beta weights indicate that Body Fat (β=0.275) was the strongest unique predictor, followed by PctSES (β=-0.207), Grade (β=-0.193), and PctMale (β=-0.067). When only the unique variance explained by each variable is examined, Body Fat (sr^2=0.055) also accounts for the most variance in Aerobic Capacity, 5.5%, followed by Grade (sr^2=0.036) with 3.6%, PctSES (sr^2=0.031) with 3.1%, and PctMale (sr^2=0.005) with 0.5%. Total unique variance was 12.7%. The semipartial correlations for BodFat, PctMale and Pct SES in the second model are less than their zero-order correlations, indicating shared variance between the variables. The semipartial correlation for Grade is slightly larger than its zero-order correlation, indicating the presence of a suppressor variable.

The multiple correlation (R=0.468) indicated a moderate positive relationship between the combination of independent variables and Aerobic Capacity. Overall, the model (R^2=0.219) explained 21.9% of the variation in Aerobic Capacity.

Model 3

For the third model, a standard regression was conducted to determine the relationship between Aerobic Capacity and PreAQI after controlling for the independent variables in Model 2 (Grade, BodFat, PctMale, PctSES). Alpha was set at 0.05. The results indicate (F(5, 16248) = 917, p<0.001) that at least one of the variables is significantly related to Aerobic Capacity.

Table 4.85
Model 3: Standard Regression of Variables (including PreAQI) for Aerobic Capacity

Variables	b	β	sr^2 (unique)	R (model)	R^2 (model)	Adjusted R^2 (model)
Grade	-2.879**	-0.193	0.0357	0.469	0.220	0.220
BodFat	0.462**	0.275	0.0557			
Pct Male	-0.203**	-0.068	0.0046			
Pct SES	-0.146**	-0.197	0.0266			
PreAQI	-0.018**	-0.037	0.0013			
	Intercept = 64.99					

***p <0.05 ** p<0.01**

As the regression coefficients in Table 4.85 indicate, all variables contributed significantly to Aerobic Capacity. Beta weights indicate that Body Fat (β=0.275) was the strongest unique predictor, followed by PctSES (β=-0.197), Grade (β=-0.193), PctMale (β=-0.068) and PreAQI (β=-0.037). When only the unique variance explained by each variable is examined, Body Fat (sr^2=0.056) also accounts for the most variance in Aerobic Capacity, 5.6%, followed by Grade

(sr^2=0.036) with 3.6%, PctSES (sr^2=0.027) with 2.7%, PctMale (sr^2=0.005) with 0.5% and PreAQI (sr^2=0.001) with 0.1%. Total unique variance was 12.4%. The semipartial correlations for BodFat, PctMale and Pct SES in the second model are less than their zero-order correlations, indicating shared variance between the variables. The semipartial correlation for Grade is slightly larger than its zero-order correlation, indicating the presence of a suppressor variable. The semipartial correlation for PreAQI approaches zero, indicating the possible presence of a spurious or intervening relationship.

The multiple correlation (R=0.469) indicated a moderate positive relationship between the combination of independent variables and Aerobic Capacity. Overall, the model (R^2=0.220) explained 22.0% of the variation in Aerobic Capacity.

The R^2 change between model 2 and model 3 was 0.001, indicating that the inclusion of PreAQI to the model added 0.1% to the explanation of the variance in the model.

4.5 Chapter Summary

This chapter presented the findings from the statistical analyses performed to evaluate the relationship between criteria air pollutants and measures of physical fitness in California school children. The study focused on four criteria air pollutants, carbon monoxide, 8-hour ozone, PM10 and PM2.5, as these are the pollutants that various California counties were in non-attainment for during the study timeframe of 2006 and 2007. Based on the literature review in Chapter 2, the statistical analyses focused on the relationship of these four pollutants with two fitness endpoints aerobic capacity and body composition passing rates. The statistical analyses were performed in accord with the four specific aims identified in Chapter 1 and the methodology specified in Chapter 3 of this report. A further discussion of the findings is available in Chapter 5.

CHAPTER V

DISCUSSION

The present study examined the association between chronic exposure to four criteria air pollutants, CO, O_3, PM_{10} and $PM_{2.5}$, and two measures of physical fitness, aerobic capacity and body composition, in California schoolchildren. To date, little research has been conducted on the effects of ambient air pollutants on the physical fitness of children. In addition, prior studies have largely focused on clinical effects following acute exposures to ambient air pollutants. This study is unique in that it assessed a functional rather than clinical measure of respiratory health following chronic exposure to criteria air pollution. By evaluating aerobic capacity, the current study assessed the association of ambient air pollution with physical performance. In addition, the current study is the first known study to evaluate the association between criteria pollutants and measures of body fat in children.

A tiered approach was used to assess the association of the four criteria air pollutants with the physical fitness outcomes. The study was divided into four different specific aims that were assessed via the statistical methods described in Section 3 of this report. The following sections summarize and discuss the implications of findings from these analyses.

5.1 Aerobic Capacity

Aerobic capacity is also referred to as VO_2max. This measure reflects the maximum rate at which oxygen can be taken up by the body and used during exercise, and is dependent on the oxygen-exchange capacity of the lungs, the oxygen-transport capacity of the cardiovascular system, and the oxygen-utilization capacity of the muscles (Welk and Meredith, 2008). For the FITNESSGRAM® physical fitness testing program, aerobic capacity is assessed using either the Progressive Aerobic Cardiovascular Endurance Run (PACER) test or a timed mile run/walk (California Department of Education, 2009a). Individual student results are compared to criterion referenced standards that represent a healthy fitness zone (HFZ) for aerobic capacity. The aggregate results (total percentage of children in the HFZ) for each grade that was assessed at a school are tracked on the California Department of Education's public Web site (California Department of Educations, 2009a). These aggregate data were the basis for the current study.

It is well established that criteria air pollutants are associated with adverse respiratory effects. To date, the majority of human studies have focused on clinical and symptomatic measures of respiratory health, such as forced vital capacity (FVC), forced expiratory volume (FEV), asthma, wheezing, and reports of shallow breathing. For the most part, these studies have focused on the appearance of these clinical effects following acute exposures to ambient air pollutants without regard to the impact of these adverse effects on fitness performance. Although clinical outcomes may be impaired by criteria air pollutants, it is not known whether these clinical effects translate to functional effects, or whether these effects persist under conditions of chronic exposure. This study was unique in that it assessed the association of chronic exposure to criteria air pollutants with a functional, rather than clinical, measure of respiratory health. Aerobic capacity in this study is a measure of the performance ability of a child under standardized physical fitness testing conditions. It stands to reason that if acute and chronic exposure to criteria air pollutants can result in adverse respiratory effects and symptoms, it may be hypothesized that these same criteria air pollutants may also be associated with decrements in aerobic capacity.

A four-tiered approach was used to assess the association between aerobic capacity and the four criteria air pollutants. The first step evaluated whether aerobic capacity passing rates differed by attainment status. Step 2 assessed various demographic variables to determine their association with aerobic capacity. The third step evaluated whether an association between aerobic capacity passing rate and the air pollutant attainment status remained after adjusting for significant demographic variables. For those criteria pollutants that were found to have a significant association in Step 3, a fourth step was performed using various environmental metrics to assess if a dose-response type assessment existed within the non-attainment areas. The following sections summarize and discuss the implications of findings from these analyses.

5.1.1 Specific Aim 1 - Aerobic Capacity by Attainment Status

The hypothesis for this specific aim stated that aerobic capacity passing rates would be higher at schools located in attainment areas and would be lower at schools in non-attainment areas, based on the assumption that these criteria air pollutants would adversely affect respiratory health leading to decreased performance in aerobic capacity testing. Assignment of a school to an attainment or non-attainment area was dependent on the county in which the school was located. For all four criteria air pollutants, a significant difference ($p<0.05$) was found in aerobic capacity passing rates, with schools located in attainment areas having a higher average passing rate than schools located in non-attainment counties. In terms of explanatory power for the t-test, 8-hour ozone had the most explanation of variance in aerobic capacity passing rate at 1.1%, followed by PM_{10} at 0.9%, $PM_{2.5}$ at 0.7%, and carbon monoxide at 0.2%.

Despite the finding of a significant difference in aerobic capacity passing rates at schools located in attainment areas versus non-attainment areas for all four criteria air pollutants, it is important to note that this finding may be confounded by other demographic factors. For example, if aerobic capacity is influenced by a variable (e.g., socioeconomic status) that is more common to a non-attainment area, the significant association seen in the t-test may in fact be due to confounding variables rather than attainment status. Specific Aim 2 was developed to identify those factors that may influence the aerobic capacity passing rates, and allow for further statistical analyses controlling for these factors as necessary.

5.1.2 Specific Aim 2 – Demographic Variables

The association between four demographic factors (gender, grade, socioeconomic status, and ethnicity) and aerobic capacity passing rates were statistically evaluated to determine which factors were significantly associated with the percentage of students passing the aerobic capacity testing at a school. The aerobic capacity endpoint was found to differ significantly ($p<0.01$) by all four demographic variables. Therefore, all were retained in the subsequent regression models. In addition, a fifth demographic variable, the percentage of students passing body composition testing at a school, was included as a demographic variable for regression modeling. Like aerobic capacity, body composition is an endpoint of interest in the current study. However, because it has been reported that excess body fat levels can adversely impact results of aerobic capacity testing (Welk and Meredith, 2008), this variable was included in the subsequent multiple regression modeling.

5.1.3 Specific Aim 3 – Multiple Regression Modeling

Although many factors could affect aerobic capacity in this study, the five demographic factors that were controlled in the multiple regression modeling were 1) percent of students passing body composition testing, 2) percentage of males at a school (gender), 3) grade, 4) percentage of students receiving free or reduced price meals at a school (socioeconomic status), and 5) percent of minorities (non-White) in the grade being evaluated at a school (ethnicity). A separate model was run for each of the four criteria air pollutants.

<u>Carbon Monoxide</u>

A statistically significant relationship between carbon monoxide attainment status and school aerobic capacity passing rates was found after adjusting for the effects of body composition, gender, grade, socioeconomic status, and ethnicity. According to the results shown in Table 4.32, we can predict that if a school is located in a non-attainment area for carbon monoxide, the overall percentage of students in a healthy fitness zone for aerobic capacity would decrease by 1.43%.

8-hour Ozone

A statistically significant relationship between 8-hour ozone attainment status and school aerobic capacity passing rates was found after adjusting for the effects of body composition, gender, grade, and socioeconomic status. In the model, ethnicity was not found to be a significant variable and was removed prior to the regression. According to the results shown in Table 4.36, we can predict that if a school is located in a non-attainment area for 8-hour ozone, the overall percentage of students in an HFZ for aerobic capacity would decrease by 2.38%.

PM_{10}

A statistically significant relationship between PM_{10} attainment status and school aerobic capacity passing rates was found after adjusting for the effects of body composition, gender, grade, socioeconomic status, and ethnicity. According to the results shown in Table 4.40, we can predict that if a school is located in a non-attainment area for PM_{10}, the overall percentage of students in an HFZ for aerobic capacity would decrease by 0.96%.

$PM_{2.5}$

After adjusting for the effects of body composition, gender, grade, socioeconomic status, and ethnicity, no significant association was found between $PM_{2.5}$ attainment status and aerobic capacity passing rates in California schools.

For all of the models, the percentage of students passing body fat testing was the strongest unique predictor of aerobic capacity passing rates. This was followed by grade and the percentage of students receiving free or reduced price meals. The next variable in terms of predictive power was the percentage of male students in the grade being evaluated, followed by the attainment status of the pollutant being assessed in the model. The percentage of minority students (non-White) at a school was the variable with the least predictive ability in all models, and was found to be non-significant for the 8-hour ozone model.

5.1.4 Specific Aim 4 – Dose-Response Evaluation

It is important to note that the significant association between carbon monoxide, 8-hour ozone, and PM_{10} attainment status and the percentages of students passing aerobic capacity fitness testing does not equal causality. In other words, we can not say that any of these pollutants caused the decreased overall aerobic capacity observed in school children, only that they are associated with this endpoint. However, we have determined that there is a significant difference in aerobic capacity passing rates between attainment and non-attainment areas for these three criteria pollutants. Therefore, it is beneficial to focus on whether a dose-response type relationship is present in the non-attainment areas. In other words, as exposure to the pollutant increases within these non-attainment areas, is there an analogous increase in the adverse effect? If the effect does not worsen as the dose or exposure increases, it is less likely that the decrease in aerobic capacity is caused by the pollutant.

In terms of chronic exposures to ambient air pollutants, it is not clear as to which metric may best predict adverse health outcomes. Therefore, several metrics were evaluated to assess whether a dose-response type relationship was present in counties that were in non-attainment for the pollutant of concern. The metrics that were selected reflect exposure in the year preceding fitness testing to determine if an association exists with aerobic capacity. Carbon monoxide could not be evaluated due to lack of data, and $PM_{2.5}$ was not significant after controlling for confounding variables in Specific Aim 3, therefore these two pollutants were not evaluated further.

The metrics that were selected for further evaluation included the number of days that a county exceeded the NAAQS standard for 8-hour ozone or the California state standard for PM_{10}, the person-days of these exceedances, and the annual average concentration for these pollutants within the county. Person-days are equivalent to the number of days the pollutant exceeds a health standard times the number of persons living in an exposed region and offer a representation of the overall population burden of air pollution exposure (California Environmental Health Investigations Branch, 2010).

A discussion of the key findings for both 8-hour ozone and PM_{10} is provided below. The aerobic capacity passing rate was controlled for key confounding demographic variables (body fat, gender, grade and socioeconomic status). Percent ethnicity was not included as a variable, as it was determined to be highly correlated (>0.7) with the metric for socioeconomic status.

In addition to examining a dose-response type relationship within these non-attainment areas, an assessment of school passing rates within all California counties was performed by evaluating the number of days that the Air Quality Index (AQI) within the county exceeded a value of 100.

Ozone

Number of days NAAQS Exceeded: The environmental metric for this assessment was the number of days that the 8-hour concentration of ozone in a non-attainment county exceeded the NAAQS standard of 0.075 ppm in the year preceding fitness testing. Inclusion of this metric to the multiple regression model added an additional 0.1% of explanation in aerobic capacity passing rates after adjusting for confounding demographic variables. Based on a significant association in the model, for each additional day that the NAAQS was exceeded in the year preceding fitness testing the average percentage of students passing aerobic capacity fitness testing at a school was decreased by 0.018%.

Person Days: When the number of days that the NAAQS was exceeded was multiplied by the population in the county to obtain a person-days metric for 8-hour ozone, there was no significant relationship observed with aerobic capacity passing rates.

Annual Average Concentration: For non-attainment counties, a significant relationship was observed between the annual average concentration of 8-hour ozone in the May to October timeframe preceding fitness testing and the aerobic capacity passing rates of schools. Inclusion of this metric added an additional 0.1% to the explanation of the variance in the model. For each 10 ppb increase in 8-hour ozone concentration, aerobic capacity pass rate were predicted to decrease by 0.5%.

$\underline{PM_{10}}$

None of the environmental metrics that were assessed for PM_{10} under this specific aim were found to be statistically significant when included in the regression models, indicating that a dose-response type relationship for these metrics was not present.

AQI

The Air Quality Index (AQI) for all California counties was used to assess aerobic capacity passing rates. This was performed by evaluating the number of days that the AQI within each county exceeded a value of 100 in the year preceding fitness testing. Inclusion of this metric in the regression model added 0.1% to the explanation of the variance in the model after adjusting for confounding demographic variables. For each additional day that the AQI exceeded a value of 100, the percentage of students in the Health Fitness Zone for aerobic capacity decreased by 0.018%.

5.1.5 Discussion

After adjustment for body fat, age, gender, ethnicity, and socioeconomic status, the attainment status for three of the four criteria air pollutants (CO, 8-hour O_3, PM_{10}) remained significantly associated with the total percentage of students at a school with aerobic capacity levels in a healthy fitness zone. Schools located in non-attainment areas for these three pollutants had lower overall passing rates than schools in attainment areas. Further review indicated that a significant dose-response type relationship was evident between aerobic capacity passing rates and measures of 8-hour ozone. No such relationship was observed for PM_{10}, and this assessment was not possible for carbon monoxide due to lack of an adequate data set for evaluation. A significant dose-response type relationship was also observed with aerobic capacity passing rates observed to decrease as the number of days exceeding an AQI of 100 increases.

<u>Carbon monoxide</u>

The toxicity of CO is attributable to its strong affinity for hemoglobin, the oxygen transporting component of red blood cells. CO binds to hemoglobin with an affinity that is 250 times higher than the binding of oxygen with hemoglobin (Brook et al., 2004). This CO-hemoglobin binding complex is referred to as carboxyhemoglobin. Formation of carboxyhemoglobin reduces the amount of hemoglobin available to carry oxygen, and also impairs the release of oxygen at the tissue level (Brook et al., 2004). Studies (Adir et al, 1999) have shown that after acute exposures to carbon monoxide, exercise performances are impaired. In the current study, schools located in areas that were in non-attainment for carbon monoxide were found to have significantly lower percentages of students passing aerobic capacity testing than schools located in attainment areas after adjustment for confounding demographic variables. During 2006, only four counties in California were designated as non-attainment for carbon monoxide. These were the large counties of Los Angeles, Orange, Riverside, and San Bernadino. Since 2007, all counties in California have been in attainment with the NAAQS for carbon monoxide.

This study was unable to assess whether a dose-response type relationship was present in the carbon monoxide non-attainment areas. Therefore, it is important to further assess this finding of an association between aerobic capacity passing rates and carbon monoxide attainment status in order to place the results into an appropriate context.

<u>8-hour ozone</u>

Ozone has been associated with a wide variety of respiratory effects. Symptoms associated with elevated exposures to ozone include respiratory irritation, coughing, wheezing, shortness of breath, constriction of the chest, nausea, and headaches (Carlisle and Sharp, 2001). Exposure to low concentrations of ozone can result in reduced lung function. Ozone causes aggravation of respiratory and cardiovascular disease and suppresses the immune defenses of the lungs, making individuals more susceptible to respiratory infections (USEPA, 2008). Animal studies have shown that long-term exposure to high levels of ozone can result in permanent structural changes of the lungs.

In the current study, schools located in areas that were in non-attainment for 8-hour ozone were found to have significantly lower percentages of students passing aerobic capacity testing than schools located in attainment areas. In addition, within the non-attainment areas a dose-response type relationship was found with aerobic capacity for two of the chronic environmental metrics that were assessed. For each additional day that the 8-hour ozone NAAQS was exceeded in the year preceding fitness testing, the average percentage of students passing aerobic capacity fitness testing at a school was decreased by 0.018%. Likewise, for each 10 ppb increase in 8-hour ozone concentration in the May-October timeframe preceding fitness testing, aerobic capacity pass rate were predicted to decrease by 0.5%. These findings indicate that chronic exposure to 8-hour ozone is associated with decrements in aerobic capacity. The availability of studies on long-term effects of ambient ozone exposure on exercise performance is limited, thereby influencing our ability to fully compare the findings of this study with others. Our results are consistent with several other studies which investigated the chronic effects of ozone exposure. Künzli et al. (1997) evaluated the relationship between lifetime cumulative exposure to ambient ozone and pulmonary function parameters. They found that for 17-21 year old, never-smoking California students, each 10 ppb increase in lifetime ozone exposure was associated with a corresponding decrease of 167 ml/sec in FEF_{75}. The corresponding effect on $FEF_{25\text{-}75}$ was a decrease of 210 ml/sec. No association was found with FVC or FEV_1. Galizia and Kinney (1999) evaluated the respiratory health of 520 Yale College students, aged 17-21, in regards to their chronic ozone exposure histories. After controlling for confounding variables (race, gender, body size, SES, and indoor environmental factors), the high exposure group was observed to have significantly diminished lung function (FEV_1 and $FEF_{25\text{-}75}$) and elevated chronic respiratory symptoms. $FEF_{25\text{-}75}$ and FEF_{75} are measures of small airway flow that are considered to be early indicators for precursors to chronic-obstructive lung disease (Künzli et al., 1997). Changes in airway flow could result in decreased physical performance, although it is unclear what level of airflow impairment is required before causing functional impacts in performance. However, low level exposures to ozone may have long-term effects on lung development in children thereby affecting performance. The findings of this study highlight the need for additional research to assess the role of ozone exposure in this regard.

The current study found similar relationships with aerobic capacity passing rate between both ozone and AQI, with each additional day that either the NAAQS for ozone is exceeded or the AQI exceeds a value of 100 resulting in a predicted decrease of 0.018% in this endpoint. AQI values exceeding 100 represent days where the air pollution levels for any one of the six criteria air pollutants exceeds its corresponding NAAQS. Ozone is the contaminant responsible for the majority of non-attainment classifications in California, so it is not surprising that the results for the AQI metric track those of ozone.

The USEPA (2010) has recently proposed tighter standards for ground-level ozone. The agency has proposed to lower the 8-hour ozone standard from 0.075 ppm to a value in the range of 0.060 to 0.070 ppm. This significant difference between aerobic capacity passing rates at schools located in attainment areas versus those in non-attainment area for 8-hour ozone for the current study used the NAAQS standard of 0.075 ppm. It is not known if a significant difference would remain if the study data were re-stratified according to a different ozone standard.

Particulate matter

Inhalation of particulate matter can result in the aggravation of respiratory and cardiovascular disease. Particulate matter has also been associated with reduced lung function, increased respiratory symptoms, and premature death (USEPA, 2008). The current study focused on two measures of particulate matter, PM_{10} and $PM_{2.5}$. Schools located in non-attainment areas for PM_{10} were found to have significantly lower percentages of students in a health fitness zone for aerobic capacity than schools located in attainment areas. However, this finding did not have a dose-response type relationship when evaluated via chronic measures of exposure from the year preceding the fitness testing. For $PM_{2.5}$, there was no significant difference between schools in attainment and non-attainment areas for this pollutant.

Our findings showed an association between aerobic capacity passing rates by attainment status for PM_{10}, a coarser particle, but not with $PM_{2.5}$, a finer particle. In contrast to the findings of the current study, research has indicated that fine particles are more closely associated with acute respiratory health effects in children than coarse particles (Florida-James et al., 2004; Rundell et al., 2008). Our finding for PM_{10} did not exhibit a dose-response type relationship within the non-attainment areas, indicating that PM_{10} may not be responsible for the finding of decreased aerobic capacity passing rates.

Numerous studies have been performed on the effects of particulate matter on respiratory health. However, few of these studies have focused on the impact of particulate matter on exercise performance. Those studies that have focused on performance have based their finding on short-term, rather than chronic exposures to these pollutants. Acute exposure to PM_{10} was found to be significantly correlated with the performance of female marathon runners. Marr and Ely (2009) found that for each 10 ug/m^3 increase in PM_{10}, there was an associated decrease in finishing time of 1.4%. The lack of an association between chronic measures of particulate matter exposure and aerobic capacity passing rates denotes the possibility that acute exposures to particulate matter are more relevant to respiratory effects and athletic performance than are chronic exposures. This could be further assessed by repeating this study using individual student results, rather than aggregated data, and adjusting for acute exposures to particulate matter on the days of or immediately preceding fitness testing.

5.2 Body Composition

The term body composition refers to the components that make up body weight, these being muscle, bone, fat, organs, skin, and nerve tissue (Welk and Meredith, 2008). In the FITNESSGRAM® testing program used by the State of California, body composition is a measure of body fatness and is estimated by either measuring skinfold thicknesses at selected sites on the body or calculating a Body Mass Index (BMI) (Welk and Meredith, 2008). The association of ambient air pollutants with this measure of body fat in California schoolchildren was evaluated in response to a recent study by Sun et al. (2009) that demonstrated increased body fat in mice exposed to air pollution in conjunction with a poor diet.

Although there may be some students who are not in a healthy fitness zone due to an extremely low percentage of body fat, a lower percentage of students passing the body composition testing is analogous to more students with excess levels of body fat at a given school.

A three-tiered approach was used to assess the association between body composition and the four criteria air pollutants. The first step evaluated whether body composition passing rates differed by attainment status. Step 2 assessed various demographic variables to determine their association with body composition. The third step evaluated whether an association between body composition passing rate and the air pollutant attainment status remained after adjusting for significant demographic variables. A fourth step was not included in this assessment, because although respiratory function may be impacted by a preceding year's pollutant concentration, it is not expected that body fat percentages would respond as rapidly to this exposure. Therefore, body composition was not assessed in the same dose-response manner as was aerobic capacity.

5.2.1 Specific Aim 1 – Body Composition by Attainment Status

For all four criteria air pollutants, a significant ($p<0.05$) difference was found in body composition passing rates at schools located in attainment versus non-attainment counties. The hypotheses for this specific aim stated that body composition passing rates would be higher at school located in attainment areas and would be lower at schools in non-attainment areas. These hypotheses were supported for all four criteria air pollutants tested. In terms of explanatory power for the t-test, PM_{10} and $PM_{2.5}$ tied for the most explanation at 2.1%, followed by 8-hour Ozone at 1.3%, and Carbon Monoxide at 0.3%.

Despite the finding of a significant difference in body composition passing rates at schools located in attainment areas versus non-attainment areas, it is important to note that this finding may be confounded by other demographic factors. For example, if body fat concentrations are influenced by a variable (e.g., socioeconomic status) that is more common to a non-attainment area, the significant association seen in the t-test may in fact be due to confounding variables.

Therefore, Specific Aim 2 was developed to identify those factors that may influence the body composition passing rates.

5.2.2 Specific Aim 2 – Demographic Variables

The association between four demographic factors (gender, grade, socioeconomic status, and ethnicity) and body composition passing rates were statistically evaluated to determine which factors were significantly associated with the percentage of students passing the body fat testing at a school. Gender, grade, socioeconomic status and ethnicity were all found to be significantly associated with body composition. Therefore, each of these factors was included in the multiple regression analyses conducted for Specific Aim 3.

5.2.3 Specific Aim 3 – Multiple Regression Modeling

Although many factors could affect body composition in this study, the four demographic factors that were controlled in the multiple regression modeling were 1) percentage of males at a school (gender), 2) grade, 3) percentage of students receiving free or reduced price meals at a school (socioeconomic status), and 4) percent of minorities (non-White) in the grade being evaluated at a school (ethnicity). A separate model was run for each of the four criteria air pollutants. Ethnicity was removed from each of the models based on its strong correlation (>0.7) with socioeconomic status.

Carbon Monoxide

A statistically significant relationship ($P<0.05$) between carbon monoxide attainment status and the percentage of students with body composition in the HFZ was found after adjusting for the effects of gender, grade, and socioeconomic status. According to the results shown in Table 4.48, we can predict that if a school is located in a non-attainment area for carbon monoxide, the overall percentage of students in an HFZ for body composition would decrease by 0.46%.

8-hour Ozone

A statistically significant relationship ($p<0.01$) between 8-hour ozone attainment status and the percentage of students with body composition in the HFZ was found after adjusting for the effects of gender, grade, and socioeconomic status. In the model, ethnicity was not found to be a significant variable and was removed prior to the regression. According to the results shown in Table 4.52, we can predict that if a school is located in a non-attainment area for 8-hour ozone, the overall percentage of students in an HFZ for body composition would decrease by 0.71%.

PM_{10}

A statistically significant relationship ($p<0.05$) between PM_{10} attainment status and the percentage of students with body composition in the HFZ was found after adjusting for the effects of gender, grade, and socioeconomic status. According to the results shown in Table 4.56, we can predict that if a school is located in a non-attainment area for PM_{10}, the overall percentage of students in an HFZ for body composition would decrease by 0.73%.

$PM_{2.5}$

A statistically significant relationship ($p<0.01$) between $PM_{2.5}$ attainment status and the percentage of students with body composition in the HFZ was found after adjusting for the effects of gender, grade, and socioeconomic status. According to the results shown in Table 4.60, we can predict that if a school is located in a non-attainment area for $PM_{2.5}$, the overall percentage of students in an HFZ for body composition would decrease by 0.70%.

For all of the models, the percentage of students receiving free or reduced price meals was the strongest unique predictor of body composition passing rates. This variable routinely explained more than 30% of the variation in body composition passing rates. This was followed by grade and the percentage of male students. The attainment status of the pollutant being assessed was the variable with the least predictive ability in all models.

5.2.4 Discussion

After adjustment for age, gender, and socioeconomic status, the attainment status for all four criteria air pollutants remained significantly associated with the total percentage of students at a school with body fat levels in a healthy fitness zone. Schools located in non-attainment areas for each of these pollutants had lower overall passing rates than schools in attainment areas, indicating that areas with higher levels of air pollution had a higher percentage of overweight children. For all four pollutants, the overall predicted difference in body composition passing rates was less than 1% between schools in attainment versus non-attainment areas.

No studies were located that have previously investigated the relationship between body fat and carbon monoxide, 8-hour ozone, or PM_{10}. Therefore the implications of these findings for these three pollutants in the current study are unclear.

Only one study was identified that investigated body fat in relation to $PM_{2.5}$ exposure. In a recent report, Sun et al. (2009) studied the interactions between exposure to $PM_{2.5}$ and metabolic determinants of obesity and insulin resistance in mice. The authors found that when mice were fed a high-fat diet over a 10-week period to induce obesity and then subsequently exposed to either filtered air or air with particulate matter ($PM_{2.5}$) for six hours a day, five days a week, over a 24-week period, the mice exposed to $PM_{2.5}$ had significant increases in visceral and mesenteric adipose mass. In other words, these mice had higher levels of body fat than mice exposed to filtered air. The air pollution level inside the chamber containing particulate matter was comparable to levels a commuter may be exposed to in many metropolitan areas in the United States, and when adjusted for the duration of daily exposure, resulted in concentrations that were below the current NAAQS recommendation of 15 ug/m^3.

Body fat is tied to many factors, including gender, physical activity, nutrition (caloric intake), and socioeconomic status. Although adjustments were made for certain demographic variables, it is possible that some other confounding variable that was not accounted for may be accountable for the finding. It is important to note that the current study utilized aggregate data at the school level and is not directly applicable to results in individual children. It is necessary to recreate these findings at the individual level prior to making conclusions about the relationship between these ambient air pollutants and body fat.

Although the full association of air pollution with measures of body fat is not known, excess body fat has been associated with increased risk factors for cardiovascular disease and increased risk of Type 2 diabetes in children and adolescents (Welk and Meredith, 2008). Additionally, a relationship between childhood obesity and subsequent obesity in adulthood has been established. Excess body fat and obesity in childhood increases the likelihood of obesity-related adult diseases including coronary heart disease, hypertension, and type II diabetes (Welk and Meredith, 2008).

5.3 Strengths and Limitations

This section describes the major strengths and limitations of the current study. Both must be carefully considered when interpreting and applying the study results.

Strengths

There are considerable strengths associated with this study. This study focused on the association of criteria air pollutants with physical fitness in children. As discussed in Section 2, children have both physiological and behavioral characteristics that make them uniquely susceptible to the effects of air pollution. Due to this susceptibility, children are an ideal study population in which to evaluate potential health effects associated with exposure to ambient air pollutants. It is anticipated that any effects from exposure to ambient air pollutants would be more likely to be present in a sensitive population than a less sensitive population.

This study utilized publicly available datasets to identify variables of importance as well as their relationships with measures of physical fitness in children. As such, data were able to be gathered in a non-intrusive manner, although the study lacked the ability to manipulate or control exposure variables. This study design allowed for a more comprehensive understanding of this issue on which to base future experimental studies. A large study population was utilized, consisting of more than 2.7 million California schoolchildren who were tested for physical fitness during 2006 and 2007. Each of the 17,293 records in the final dataset represented the fitness testing results for a grade within a corresponding school.

This study allowed for adjustment of potential confounding factors, such as gender, age, ethnicity and socioeconomic status. Each of these factors was determined to have a significant association with both aerobic capacity and body composition passing rates.

Air pollution has been a long-standing concern in California. During 2006 and 2007, numerous California counties were classified as non-attainment areas for carbon monoxide, ozone, and particulate matter. The lack of attainment in certain counties provided the comparison groups for fitness testing results by attainment status. In addition, the extensive air monitoring network in California led to the availability of a robust dataset for annual average concentrations and the frequency of days exceeding air quality standards in the majority of California counties.

Limitations

Despite the considerable strengths of the current study, there are also several key limitations that must be considered. First and foremost is the fact that the study was based on summary statistics of results from physical fitness testing. Data were not available at the individual child level and were instead available at an aggregate level for each evaluated grade within a school. Prior to basing conclusions on the findings in this study, these results should be replicated at the individual student level.

The current study was an ecologic epidemiologic study. Ecologic tests are not designed for developing an effects threshold. These studies are useful in establishing an association, but do not have causal interpretation, nor do they establish a threshold. Ecologic studies are designed to correlate aggregate exposure data with aggregate health data for each unit of observation (e.g., counties) (Mather et al., 2004). Therefore, although it is possible to determine whether the changes in exposure to criteria air pollutants are correlated with physical fitness achievement, it is not possible to assess the concentration at which physical fitness measures are adversely impacted. Significant findings cannot be assumed to be causal without further experimental study.

It is possible that children within the study, as well as the schools themselves, were subject to exposure misclassification. The use of aggregate fitness testing data for each school was based on the assumption that the children attending the school resided in the county in which the school was located. In addition, concentration of air contaminants is not homogeneous and will be expected to vary throughout a county depending on factors such as emissions sources, weather, and topography. Use of one value to represent the county will result in some schools being overestimated as to their exposure and others being underestimated as to true exposure levels.

Although the study controlled for several demographic variables known to be associated with aerobic capacity and body composition, there was no ability to control for several additional factors that be associated with these endpoints, including nutritional status, genetic factors, and exposure to second-hand smoke. In addition, there was no way to control for exposures to additional source contributions of the criteria air pollutants that were not accounted for in the environmental metrics in this study.

This study focused on the association of single pollutants with aerobic capacity and body composition passing rates. It did not evaluate the effects of exposures to mixtures of pollutants. Because humans are simultaneously exposed to a complex mixture of air pollutants, many of which may have impacts on respiratory health, there may be a combined effect which is not accounted for in the current study.

Despite these limitations, the current study offers a further insight into the association between criteria air pollutants and physical fitness in children.

5.4 Recommendations

The following recommendations are based upon the results of this research and are intended to guide the application and communication of these findings, as well as promote further research on this important issue.

5.4.1 Application of Current Findings

This study utilized publicly available datasets to identify variables of importance as well as their relationships with aggregate measures of physical fitness. Variables that were assessed in this study included gender, age, ethnicity, socioeconomic status, and various environmental metrics for carbon monoxide, ozone, and particulate matter. Although findings from this study can not be applied directly at the individual student level, they can be used to drive future research on the effects of criteria air pollutants in children.

In addition, findings from this study can be used to drive future programs to improve physical fitness in children by focusing on those factors that have the most influence on this endpoint.

According to the research findings supplied in Chapter IV of this report, percent body fat, age, and socioeconomic status were the strongest unique predictors of aerobic capacity passing rates at a school. Although the associations between aerobic capacity passing rates and attainment status for carbon monoxide, 8-hour ozone, and PM_{10} attainment status were significant, these associations were small in comparison to the contribution to the models from body fat and socioeconomic status. This indicates that more emphasis should be placed on determining how to overcome the negative consequences of increased body fat and lower socioeconomic status on aerobic capacity.

For the portion of this study that focused on body composition passing rates, it was determined that the measure of socioeconomic status was the largest contributing factor to the multiple regression model, with approximately 30-35% of the unique variation in body composition explained by this factor. In comparison, the attainment status for carbon monoxide, 8-hour ozone, PM_{10} and $PM_{2.5}$ explained the least unique variation in each model explaining 0.03%, 0.03%, 0.09%, and 0.08%, respectively.

In discussion the implications of findings of this research, this report does not include policy recommendations for criteria air pollutants. Kheifets et al. (2001) offer a detailed discussion on the merits of including policy statements in the epidemiological research of electric and magnetic fields (EMF). In their discussion, Kheifets et al. (2001) state that *"The types of policy statements made in the discussion sections of research papers are usually too general to be of much practical utility, since not all of the options and facts required to determine the implications of the research for policy alternatives are available."* For the current study, it is agreed that the analysis of such questions as whether air quality standards are sufficient to protect health or whether criteria air pollutants cause decrements in physical fitness of California school children exceed the limits of these research findings.

5.4.2 Communication of Findings

In order to be valuable, research findings have to be communicated. According to the Social Issues Research Centre (SIRC, 2001), research findings should be communicated accurately and in a manner that minimizes any potential for distorted or unwarranted interpretations. SIRC (2001) indicates that this responsibility is particularly important for research in the fields of medical and biological sciences, as members of the public may view the findings as having direct relevance to their own circumstances, activities or way of life. According to Kheifets et al. (2001), "*the degree to which the public is concerned about an epidemiologic issue depends upon its perception of the associated risks.*" One could also argue that the degree of concern is not only dependent upon the perception of risk, but is also linked to the perceived "worth" of the individual impacted by the risk. The current study focused on health outcomes in children. Children are highly valued in modern society, with policies and procedures often developed to afford protection to this group of individuals. It is therefore particularly important that any research findings that implicate hazards to this population be communicated clearly and accurately. The following provides a discussion on how the findings of the research can be appropriately communicated.

It is important to recognize that this study was based on aggregate fitness data at the school, rather than the individual, level. Therefore, the findings of this research are not directly applicable to individual children. They apply only to the schools that were evaluated. In addition, this study was not an experimental design. Therefore, although the findings demonstrate an association between certain criteria air pollutants and measures of physical fitness, this association can not be interpreted as the pollutants having caused the decrease in the percentage of students in a healthy fitness zone for aerobic capacity or body composition.

As Section 5.3 indicates, there were substantial limitations associated with this study. Although the study provides a useful insight into the association between criteria air pollutants and measures of physical fitness, communication of the results must be accompanied by a transparent disclosure of these study limitations.

In communicating these results, it is appropriate to state that, in this study, carbon monoxide attainment status was significantly associated with aerobic capacity passing rates in California schools, and that schools located in non-attainment areas had overall lower percentages of students in a health fitness zone for this endpoint than schools located in attainment areas. It is not appropriate to state that exposure to carbon monoxide caused these decreases in the percentage of students in health fitness zones for aerobic capacity. It is also inappropriate to surmise that an individual student will experience decreased aerobic capacity resulting from exposure to carbon monoxide. Similarly worded statements can be utilized for the other criteria pollutants and endpoints evaluated in this study.

As discussed previously, this study was unique in that it assessed a functional rather than clinical measure of respiratory health following chronic exposure to criteria air pollution. In addition, the current study is the first known study to evaluate the association between criteria pollutants and measures of body fat in children. Because the study is unique in many ways, it is important for these findings to be replicated in future studies.

Recommendations developed by Kheifets et al. (2001) for effective communication of scientific findings include: 1) determining the target audience(s); 2) developing the appropriate perspective for the research findings; 3) setting the study in its clinical context; and 4) using simple, rather than complex, language to convey the message.

5.4.3 Recommendations for Further Study

This study suggests that chronic exposures to certain criteria air pollutants may be a factor in decrements in childhood physical fitness. The majority of recommendations for further study focus on replicating the current findings as well as overcoming identified study limitations.

- The findings of the current study are limited to demonstrating an association and not causality between exposure to criteria air pollutants and decreased fitness levels. Additional evidence and the use of an experimental study design is needed to demonstrate whether the criteria air pollutants that were found to be significantly associated with measures of physical fitness have a cause and effect relationship.

- It is recommended that further evaluations be performed in this study population. However, rather than using aggregate school-level data, the focus should be on individual student responses. This will allow for more accurate adjustment of confounding variables, such as age, gender, socioeconomic status, and ethnicity on an individual rather than aggregate basis, and allow for the development of more precise models to predict health outcome.

- This study was controlled for factors of gender, grade, ethnicity and socioeconomic status. Future studies could incorporate those additional variables that could not be accounted for in this study, but that have been reported to be associated with physical fitness outcomes.

- The effects of multiple pollutants on measures of aerobic capacity and body composition should be assessed. This study focused on single pollutant exposures and did not assess effects associated with multiple pollutant exposures.

- Potential exposure misclassification deficits should be minimized by obtaining or conducting more localized exposure monitoring.

5.5 Conclusions

A further understanding of the relationship between levels of criteria air pollutants and the physical fitness of children has significant implications. Reports indicate that overall student health is on the decline and that childhood obesity is currently one of the most significant public health concerns in the United States (Ogden et al., 2006). To date, there is no clear consensus regarding the effects of ambient air pollution on athletic performance and physical fitness. However, criteria air pollutants have been associated with health effects (e.g., asthma, respiratory impairment) that would certainly be expected to result in reduced athletic performance.

The results of this study suggest that certain criteria air pollutants may adversely influence the physical fitness of children. When properly adjusted for a number of associated confounders, the results of this study support the hypothesis that increases in ambient air pollutant concentrations are associated with decreased aerobic capacity and increased body fat in California schoolchildren. Schools located in non-attainment counties for carbon monoxide, 8-hour ozone, and PM_{10} had lower percentages of children passing aerobic capacity fitness testing than did schools located in attainment counties. $PM_{2.5}$ attainment status was not significantly associated with aerobic capacity passing rates. Passing rates for body composition testing were lower in schools located in non-attainment zones for all criteria air pollutants (CO, 8-hour O_3, PM_{10}, $PM_{2.5}$) evaluated in this study. Although the study design does not allow for causal determination of this relationship, further evaluation showed that a significant dose-response type relationship with aerobic capacity passing rates was present for 8-hour ozone. This association was found for both the number of days that 8-hour ozone concentrations exceeded the NAAQS in the year preceding fitness testing and the annual average concentration of ozone in the year preceding fitness testing. No dose-response type relationship was observed for aerobic capacity passing rates with varying levels of PM_{10}.

This study found that gender, grade, socioeconomic status, and ethnicity were significantly associated with both aerobic capacity and body composition passing rates. Body fat was also a significant factor for aerobic capacity passing rates. These variables, with the exception of ethnicity, each contributed more to the explanation of variance in the multiple regression models than did the attainment status of the criteria air pollutants that were evaluated.

Decreases in athletic performance and increased body fat levels in children could be predictive of the potential for adult illnesses, such as cardiovascular disease (CVD), morbidity and mortality from Type II diabetes, and other chronic ailments (Eisenmann et al., 2005; Ortega et al., 2005; Velasquez-Mieyer et al., 2005). In summary, this study provided an opportunity to further understand the association between childhood physical fitness and four criteria air pollutants, carbon monoxide, 8-hour ozone, PM_{10} and $PM_{2.5}$ in California. The findings from this study can serve as a basis to develop and implement further research in this field.

REFERENCES

Adir, Yocahi, Amnon Merdler, Simona Ben Haim, Avi Front, Ruth Harduf, and Haim Bitterman. 1999. Effects of Exposure to Low Concentrations of Carbon Monoxide on Exercise Performance and Myocardial Perfusion in Young Health Men. *Occup Environ Med*. 56:535-8.

AirNow. 2010. Air Quality Index (AQI) - A Guide to Air Quality and Your Health. Accessed online at: http://www.airnow.gov/index.cfm?action=aqibasics.aqi

American Lung Association (ALA). 2009. State of the Air. Accessed online at: http://www.lungusa2.org/sota//2009/SOTA-2009-Full-Print.pdf

American Lung Association (ALA). 2000. American Lung Association® Fact Sheet: Children and Ozone Air Pollution.

Branis, Martin, Jirı Safraek, and Adela Hytychova. 2009. Exposure of children to airborne particulate matter of different size fractions during indoor physical education at school, *Building and Environment* 44:1246–52.

Brook, Robert D., Barry Franklin, Wayne Cascio, Yuling Hong, George Howard, Michael Lipsett, Russell Luepker, Murray Mittleman, Jonathan Samet, Sidney C. Smith, Jr, and Ira Tager. 2004. Air Pollution and Cardiovascular Disease: A Statement for Healthcare Professionals From the Expert Panel on Population and Prevention Science of the American Heart Association, *Circulation* 109:2655-71.

Calderón-Garcidueñas, Lilian , Antonieta Mora-Tiscareño, Lynn A. Fordham, Charles J. Chung, Gildardo Valencia-Salazar, Silvia Flores-Gómez, Anna C. Solt, Alberto Gomez-del Campo, Ricardo Jardón-Torres, Carlos Henríquez-Roldán, Milan J. Hazucha, and William Reed. 2006. Lung Radiology and Pulmonary Function of Children Chronically Exposed to Air Pollution, *Environmental Health Perspectives* 114(9):1432-7.

California Air Resources Board. 2009. Website of the California Air Resources Board. Accessed online September 28, 2009 at: http://www.arb.ca.gov/desig/adm/define.htm

California Air Resources Board. 2008. Ambient Air Quality Standards. Accessed online on September 28, 2009 at: http://www.arb.ca.gov/research/aaqs/aaqs2.pdf

California Department of Education. 2009a. Physical Fitness Testing: Program Overview. Accessed online at: http://www.cde.ca.gov/ta/tg/pf/pftprogram.asp

California Department of Education. 2009b. Education Code Section 60800. Accessed online on September 1, 2009 at: http://www.cde.ca.gov/ta/tg/pf/pftec60800.asp

California Department of Education. 2009c. Free/Reduced Meals Program & CalWORKS Data Files. Accessed online on December 7, 2009 at: http://www.cde.ca.gov/ds/sh/cw/filesafdc.asp

California Department of Education. 2010. Physical Fitness Test (PFT) 2009-2010 Training. Accessed online on March 31, 2010 at: http://www.pft-info.org/home1.aspx

Carlisle, A J and N C C Sharp. 2001. Exercise and outdoor ambient air pollution, *Br J Sports Med.* 35:214–22.

California Environmental Health Investigations Branch. 2010. Air Quality Data Query. Accessed online on January 28, 2010 at http://www.ehib.org/page.jsp?page_key=20

Chen, Pau-Chung, Yu-Min Lai, Chang-Chuan Chan, Jing-Shiang Hwang, Chun-Yuh Yang, and Jung-Der Wang. 1999. Short-Term Effect of Ozone on the Pulmonary Function of Children in Primary School, *Environmental Health Perspectives* 107(11):921-5.

Chomitz, Virginia R., Meghan M. Slining, Robert J. McGowan, Suzanne E. Mitchell, Glen F. Dawson, and Karen A. Hacker. 2009. Is There a Relationship Between Physical Fitness and Academic Achievement? Positive Results From Public School Children in the Northeastern United States, *Journal of School Health* 79(1): 30-7.

CMA Foundation. 2008. California Association of Health Plans & California Medical Association Foundation Team Up to Combat Obesity. Press Release. March 25, 2008. http://www.calhealthplans.org/documents/01_ObsityPrsRlse032508.pdf

Drewnowski, Adam, Colin Rehm, Chi Kao and Harold Goldstein. 2009. Poverty and childhood overweight in California Assembly districts, *Health & Place* 15(2):631-5.

Drinkard B, McDuffie J, McCann S, et al. 2001. Relationships between walk/run performance and cardiorespiratory fitness in adolescents who are overweight. *Phys Ther.* 81:1889–96.

Eisenmann, Joey C., Eric E. Wickel, Gregory J. Welk, and Steven N. Blair. 2005. Relationship between adolescent fitness and fatness and cardiovascular disease risk factors in adulthood: The Aerobics Center Longitudinal Study (ACLS), *American Heart Journal* 149(1):46-53.

Florida-James, Geraint, Ken Donaldson, and Vicki Stone. 2004. Athens 2004: the Pollution Climate and Athletic Performance, J*ournal of Sports Sciences* 22(10) 967-80.

Folinsbee, Lawrence J. 1993. Human Health Effects of Air Pollution, *Environmental Health Perspectives* 100:45-56.

Foxcroft, WJ and WC Adams. 1986. Effects of Ozone Exposure on Four Consecutive Days on Work Performance and VO2max. *Journal of Applied Physiology* 61(3) 960-6.

Frankfort-Nachmias, Chava & Leon-Guerrero, A. (2002). *Social statistics for a diverse society.* 3rd ed. Thousand Oaks: Sage Publications.

Frye, Christian, Bernd Hoelscher, Josef Cyrys, Matthias Wjst, H-Erich Wichmann, and Joachim Heinrich. 2003. Association of Lung Function with Declining Ambient Air Pollution. *Environmental Health Perspectives* 111(3):383–7.

Galizia, Audrey and Patrick L. Kinney. 1999. Long-Term Residence in Areas of High Ozone: Associations with Respiratory Health in a Nationwide Sample of Nonsmoking Young Adults. *Environmental Health Perspectives* 107(8):675-9.

Gauderman, James W., Edward Avol, Frank Gilliland, Hita Vora, Duncan Thomas, Kiros Berhane, Rob McConnell, Nino Kuenzli, Fred Lurmann, Edward Rappaport, Helene Margolis, David Bates, and John Peters. The Effect of Air Pollution on Lung Development from 10 to 18 Years of Age, *The New England Journal of Medicine* 351(11):1057-67.

Gilliland, Frank D., Rob McConnell, John Peters, Henry Gong, Jr. 1999. A Theoretical Basis for Investigating Ambient Air Pollution and Children's Respiratory Health, *Environmental Health Perspectives* 107(3):403-7.

Girardot, Steven P., P. Barry Ryan, Susan M. Smith, Wayne T. Davis, Charles B. Hamilton, Richard A. Obenour, James R. Renfro, Kimberly A. Tromatore, and Gregory D. Reed. 2006. Ozone and $PM_{2.5}$ Exposure and Acute Pulmonary Health Effects: A Study of Hikers in the Great Smoky Mountains National Park, *Environmental Health Perspectives* 114(7):1044-52.

Goldberg, Mark S., Richard T. Burnett, Jeffrey Brook, John C. Bailar III, Marie-France Valois, and Renaud Vincent. 2001. Associations between Daily Cause-specific Mortality and Concentrations of Ground-level Ozone in Montreal, Quebec, *American Journal of Epidemiology* 154(9):817-26.

Gorman, Nicholas, Jeffery A. Lackney, Kimberly Rollings, and Terry T.-K. Huang. 2007. Designer Schools: The Role of School Space and Architecture in Obesity Prevention, *Obesity* 15(11):2521-30.

Harrison, Roy M. and Jianxin Yin. 2000. Particulate matter in the atmosphere: which particle properties are important for its effects on health?, *The Science of the Total Environment* 249:85-101.

Hong, YC, SS Hwang, JH Kim, KH Lee, HJ Lee, KH Lee, SD Yu, and DS Kim. 2007. Metals in Particulate Pollutants Affect Peak Expiratory Flow of Schoolchildren. *Environmental Health Perspectives* 115(3):430-4.

Jedrychowski, Wieslaw, Elzbieta Flak, and Elzbieta Mroz. 1999. The Adverse Effect of Low Levels of Ambient Air Pollutants on Lung Function Growth in Preadolescent Children, *Environmental Health Perspectives* 107(8):669-74.

Johnson, Jr , Robert L. 2004. Relative Effects of Air Pollution on Lungs and Heart, *Circulation* 109:5-7.

Kampa, Marilena and Elias Castanas. 2008. Human health effects of air pollution, *Environmental Pollution* 151:362-7.

Kapposa, Andreas D., Peter Bruckmann, Thomas Eikmann, Norbert Englert, Uwe Heinrich, Peter Hoppe, Eckehard Koch, Georg H. M. Krause, Wolfgang G. Kreyling, Knut Rauchfuss, Peter Rombout, Verena Schulz-Klemp, Wolf R. Thiel, and H.-Erich Wichmann. 2004. Health Effects of Particles in Ambient Air, Int. J. Hyg. *Environ. Health.* 207:399-407.

Kheifets, Leeka I. , Raymond S. Greenberg, Raymond R. Neutra, Gordon L. Hester, Charles L. Poole, David P. Rall, and Gail Lundell. 2001. Electric and Magnetic Fields and Cancer: Case Study. *Am. J. Epid.* 154(12):S50-9. Accessed online at: http://aje.oxfordjournals.org/cgi/reprint/154/12/S50.pdf

Kim, Janice J., Michael W. Shannon, Dana Best, Helen J. Binns, Christine L. Johnson, Lynnette J. Mazur, David W. Reynolds, James R. Roberts, William B. Weil, Sophie J. Balk, Mark Miller, and Katherine M. Shea. 2004. Ambient Air Pollution: Health Hazards to Children, *Pediatrics* 114:1699-1707.

Kinney, Patrick L., George D. Thurston, and Mark Raizenne. 1996. The Effects of Ambient Ozone on Lung Function in Children: A Reanalysis of Six Summer Camp Studies. *Environmental Health Perspectives* 104(2):170-4.

Kippelen, P., C. Caillaud, E. Robert, P. Connes, P. Godard and C. Prefaut. 2005. Effect of Endurance Training on Lung Function: A One Year Study, *Br. J. Sports Med.* 39:617-21.

Kulkarni, Neeta and Jonathan Grigg. 2008. Effect of Air Pollution on Children. *Paediatrics and Child Health* 18(5):238-43.

Künzli, Nino, Fred Lurmann, Mark Segal, Long Ngo, John Balmes, and Ira B. Tager. 1997. Association Between Lifetime Ambient Ozone Exposure and Pulmonary Function in College Freshman – Results of a Pilot Study. *Environ. Res.* 72:8-23.

Lee, Nolan E., K. De Anindaya, and Paul A. Simon. 2006. School-Based Physical Fitness Testing Identifies Large Disparities in Childhood Overweight in Los Angeles, *Journal of the American Dietetic Association* January 2006:118-21.

Lee-Jane, Sally Liu, Ralph Delfino, and Petros Koutrakis. 1997. Ozone Exposure Assessment in a Southern California Community, *Environmental Health Perspectives* 105(1):58-65.

Lin, Shao, Xiu Liu, Linh H. Le., and Syni-An Hwang. 2008. Chronic Exposure to Ambient Ozone and Asthma Hospital Admissions Among Children. *Environmental Health Perspectives* 116(12):1725-30.

Maes HH, MC Neale, and LJ Eaves. 1997. Genetic and environmental factors in relative body weight and human adiposity. *Behav Genet* 27: 325–51.

Marr LC and MR Ely. 2009. The Effect of Air Pollution on Marathon Running Performance. *Med Sci Sports Exerc.* 42(3):585-91.

McMurray, Robert G., Joanne S. Harrell, Shibing Deng, Chyrise B. Bradley, Lori M. Cox, and Shrikant I. Bangdiwala. 2000. The Influence of Physical Activity, Socioeconomic Status, and Ethnicity on the Weight Status of Adolescents. *Obesity Research* 8(2): 130-9.

Meredith, Marilu D. 2008. Parental Overview of FITNESSGRAM Assessment. The Cooper Institute. Accessed online at:
http://www.cooperinstitute.org/products/grams/documents/ParentOverview.pdf

Mittleman, Murray A. 2007. Air Pollution, Exercise, and Cardiovascular Risk, *The New England Journal of Medicine* 357(11):1147.

Neidell, Matthew J. 2002. Air Pollution, Health, and Socio-Economic Status: The Effect of Outdoor Air Quality on Childhood Asthma. Working Paper Number 805. Department of Economics. University of California, Los Angeles.

Norman, Anne-Caroline, Bart Drinkard, Jennifer R. McDuffie, Samareh Ghorbani, Lisa B. Yanoff, and Jack A. Yanovski. 2005. Influence of Excess Adiposity on Exercise Fitness and Performance in Overweight Children and Adolescents. *Pediatrics* 115(6): e690-6.

Ogden, Cynthia L., Margaret D. Carroll, Lester R. Curtin, Margaret A. McDowell, Carolyn J. Tabak, and Katherine M. Flegal. 2006. Prevalence of Overweight and Obesity in the United States, 1999-2004, *Journal of the American Medical Association* 295(13):1549-55.

O'Neill, Marie S., Aristidis Veves, Antonella Zanobetti, Jeremy A. Sarnat, Diane R. Gold, Panayiotis A. Economides, Edward S. Horton and Joel Schwartz. 2005. Diabetes Enhances Vulnerability to Particulate Air Pollution–Associated Impairment in Vascular Reactivity and Endothelial Function, *Circulation* 111:2913-20.

Ortega, Francisco B., Jonatan R. Ruiz, Manuel J. Castillo, Luis A. Moreno, Marcela González-Gross, Julia Wärnberg, Ángel Gutiérrez and the AVENA Group. 2005. Low Level of Physical

Fitness in Spanish Adolescents. Relevance for Future Cardiovascular Health (AVENA Study), *Revista Espanola de Cardiologia* 58(8):898-909.

Park, Hyoungsook and Namhee Kim. 2008. Predicting Factors of Physical Activity in Adolescents: A Systematic Review, *Asian Nursing Research* 2(2):113-28.

Patrick, Lyn. 2006. Lead Toxicity, A Review of the Literature. Part I: Exposure, Evaluation, and Treatment, *Alternative Medicine Review* 11(1):2-18.

Pivarnik, James M. and Karin A. Pfeiffer. 2002. Position Paper: The Importance of Physical Activity for Children and Youth. Michigan Governor's Council on Physical Fitness, Health and Sports. July 2002. Michigan Fitness Foundation. Accessed online at: http://www.michiganfitness.org/Publications/documents/Adolescents.pdf

Powell, Kenneth E., Alice M. Roberts, James G. Ross, Mary Ann C. Phillips, Dawud A. Ujamaa, and Mei Zhou. 2009. Low Physical Fitness Among Fifth- and Seventh-Grade Students, Georgia, 2006, *American Journal of Preventive Medicine* 36(4):304-10.

Reigart, J. Routt, Ruth A. Etzel, Lynn R. Goldman, Jim G. Hendrick, Howard C. Mofenson, and Peter R. Simon. 1993. Ambient Air Pollution: Respiratory Hazards to Children, *Pediatrics* 91(6):1210-13.

Rodriguez, Clemencia, Russell Tonkin, Jane Heyworth, Merci Kusel, Nick De Klerk, Peter D. Sly, Peter Franklin, Tina Runnion, Adrian Blodkley, Louis Landau, and Andrea L. Hinwood. 2007. The Relationship Between Outdoor Air Quality and Respiratory Symptoms in Young Children, *International Journal of Environmental Health Research* 17(5):1-10.

Rundell, Kenneth W. 2004. Pulmonary Function Decay in Women Ice Hockey Players: Is There a Relationship to Ice Rink Air Quality? *Inhalation Toxicology* 16:117-23.

Rundell, Kenneth W., Renee Caviston, Amanda M. Hollenbach, and Kerri Murphy. 2006. Vehicular Air Pollution, Playgrounds, and Youth Athletic Fields, *Inhalation Toxicology* 18:541–7.

Rundell, Kenneth W., Josh B. Slee, Renee Caviston, and Amanda M. Hollenbach. 2008. Decreased Lung Function After Inhalation of Ultrafine and Fine Particulate Matter During Exercise is Related to Decreased Total Nitrate in Exhaled Breath Condensate. *Inhalation Toxicology* 20:1-9.

Salvi, Sundeep. 2007. Health effects of ambient air pollution in children, Paediatric Respiratory Reviews. 8:275–80.

Schoenherr, Allan A. 1992. A Natural History of California. Second Edition. California Natural History Guides, University of California Press, Berkeley, Los Angeles, London. ISBN: 0520069226. 772pp. Accessed online at:
http://books.google.com/books?id=hk66OIHoesEC&pg=PA401&lpg=PA401&dq=%22air+pollution%22+california+history&source=bl&ots=JUG8EgX5U4&sig=XOlz3nulvRRmUbXtJ_G0tg1zXKw&hl=en&ei=dV6cSoinBMfwnQe-rOmVCA&sa=X&oi=book_result&ct=result&resnum=4#v=onepage&q=&f=false

Sharman, James E. 2005. Clinicians prescribing exercise: is air pollution a hazard?, *MJA* 182(12):606-7.

Simkhovich, Boris Z., Michael T. Kleinman, and Robert A. Kloner. 2008. Air Pollution and Cardiovascular Injury: Epidemiology, Toxicology, and Mechanisms, *Journal of the American College of Cardiology* 52(9):719-26.

Singh, Sangeeta and Shari McMahan. 2006. An Evaluation of the Relationship between Academic Performance and Physical Fitness Measures in California Schools. *Californian Journal of Health Promotion* 4(2): 207-14.

SIRC. 2001. Guidelines on science and health communication. Prepared by the Social Issues Research Centre in partnership with the Royal Society and the Royal Institution of Great Britain. ISBN 0 85403 570 2. Accessed online at: http://www.sirc.org/publik/revised_guidelines.pdf

Sørensen, Mette, Herman Autrup, Peter Møller, Ole Hertel, Steen Solvang Jensen, Peter Vinzents, Lisbeth E. Knudsen, and Steffen Loft. 2003. Linking exposure to environmental pollutants with biological effects, *Mutation Research* 544: 255–271.

State of California. 2009. What are Air Contaminants?, California Environmental Health Investigation Branch. June 22, 2009/ Accessed online Sept. 13, 2009 at: http://www.ehib.org/page.jsp?page_key=149

Sun, Qinghua, Peibin Yue, Jeffrey A. Deiuliis, Carey N. Lumeng, Thomas Kampfrath, Michael B. Mikolaj, Ying Cai, Michael C. Ostrowski, Bo Lu, Sampath Parthasarathy, Robert D. Brook, Susan D. Moffatt-Bruce, Lung Chi Chen and Sanjay Rajagopalan. 2009. Ambient Air Pollution Exaggerates Adipose Inflammation and Insulin Resistance in Mouse Model of Diet-Induced Obesity, *Circulation* 119:538-46.

Tabachnick, Barbara G. and Linda S. Fidell. 1996. *Using Multivariate Statistics.* Third Edition. HarperCollins College Publishers. New York, NY.

Tsimeas, PD, AL Tsiokanos, Y Koutedakis, N Tsigilis and S Kellis. 2005. Does Living in Urban or Rural Settings Affect Aspects of Physical Fitness in Children? An Allometric Approach. *Br. J. Sports Med.* 39:671-4.

The California Endowment. 2005. Preventing Obesity in California: A Call for Policy and Community-Based Approaches. HEALTH….In Brief. 4(1):1-4.

US Environmental Protection Agency. 2010. Ground Level Ozone: Regulatory Actions. Accessed online at: http://www.epa.gov/glo/actions.html

US Environmental Protection Agency. 2009a. National Ambient Air Quality Standards (NAAQS). Accessed online Sept. 13, 2009 at: http://www.epa.gov/air/criteria.html#2

US Environmental Protection Agency. 2009b. Green Book: Nonattainment Status for Each County by Year. Accessed online November 10, 2009 at: http://www.epa.gov/oar/oaqps/greenbk/anay.html

US Environmental Protection Agency. 2009c. AirData. Air Quality Index Report. Accessed online December 30, 2009 at: http://www.epa.gov/oar/data/monaqi.html?st~CA~California

US Environmental Protection Agency. 2008. National air quality: Status and Trends through 2007. Research Triangle Park, NC: Environmental Protection Agency; 2008. Publication No. EPA-454/R-08-006. Available at: www.epa.gov/airtrends/reports.html Accessed August 30, 2009.

US Environmental Protection Agency. 2006. Review of the Process for Setting National Ambient Air Quality Standards. Prepared by the NAAQS Process Review Workgroup for the Assistant Administrators of the Offices of Air and Radiation and Research and Development. Accessed online at: http://www.epa.gov/ttnnaaqs/pdfs/naaqs_process_report_march2006.pdf

Velasquez-Mieyer, Pedro, Sylvia Perez-Faustinelli, and Patricia A.Cowan. 2005. Identifying Children at Risk for Obesity, Type 2 Diabetes, and Cardiovascular Disease. *Diabetes Spectrum* 18(4):213-20.

Wargo, Jane D. 2007. A History of the President's Council on Physical Fitness and Sports. Research Digest. Series 8, No. 1. March 2007. US Dept. of Health and Human Services. Accessed online at: http://www.fitness.gov/digests/March2007Digest.pdf

Welk, G. J., Meredith, M.D. (Eds.). (2008). Fitnessgram / Activitygram Reference Guide. Dallas, TX: The Cooper Institute. Accessed online on September 13, 2009 at: http://www.cooperinstitute.org/products/grams/references.cfm

Wilson, J. Gaines, Simon Kinghama, Jamie Pearcea, and Andrew P. Sturmana. 2005. A review of intraurban variations in particulate air pollution: Implications for epidemiological research, *Atmospheric Environment* 39:6444–62.

Wong, Eva Y., Julia Gohlke, William C. Griffith, Scott Farrow, and Elaine M. Faustman. 2004. Assessing the Health Benefits of Air Pollution Reduction for Children, *Environmental Health Perspectives* 112(2):226-32.

Wu, Jun, Fred Lurmann, Arthur Winer, Rong Lu, Richard Turco, and Tami Funk. 2005. Development of an Individual Exposure Model for Application to the Southern California Children's Health Study, *Atmospheric Environment* 39:259–73.

APPENDICES

APPENDIX A

Acronyms and Abbreviations

ALA	American Lung Association
AQI	Air Quality Index
ARB	California Air Resources Board
ATT	attainment
CDC	Centers for Disease Control and Prevention
CDE	California Department of Education
CO	carbon monoxide
COHb	carboxyhemoglobin
CVD	cardiovascular disease
FEF_{25}	forced expiratory flow between 25 and 75% of vital capacity
FEF_{25-75}	forced expiratory flow at 25% of vital capacity
FEV_1	forced expiratory volume in one second
FRPM	free or reduced price meal
FVC	forced vital capacity
HFZ	health fitness zone
mg/m^3	milligrams per cubic meter
NAAQS	National Ambient Air Quality Standard
NHANES	National Health and Nutrition Examination Survey
NO_2	nitrogen dioxide
O_3	ozone
PACER	Progressive Aerobic Cardiovascular Endurance Run
Pb	lead
PEFR	peak expiratory flow rate
PFT	physical fitness testing
PM_1	particulate matter with average size of 1 microns or less
PM_{10}	particulate matter with average size of 10 microns or less
$PM_{2.5}$	particulate matter with average size of 2.5 microns or less
ppb	parts per billion
ppm	parts per million
SES	socioeconomic status
SO_2	sulfur dioxide
TSP	total suspended particulates
ug/m3	micrograms per cubic meter
USEPA	United States Environmental Protection Agency
VO_2max	aerobic capacity
VOC	volatile organic compound

Note: Study variables and their corresponding abbreviations are defined in Chapter 3

APPENDIX B

Summary of California Counties by Attainment Status

California Counties by Attainment Status (2006-2007)

County Name	ccode	8hrO3ATT	COATT	PM10ATT	PM25ATT
Alameda	1	2006,2007			
Alpine	2				
Amador	3	2006,2007			
Butte	4	2006,2007			
Calaveras	5	2006,2007			
Colusa	6				
Contra Costa	7	2006,2007			
Del Norte	8				
El Dorado	9	2006,2007			
Fresno	10	2006,2007		2006,2007	2006,2007
Glenn	11				
Humboldt	12				
Imperial	13	2006,2007		2006,2007	
Inyo	14			2006,2007	
Kern	15	2006,2007		2006,2007	2006,2007
Kings	16	2006,2007		2006,2007	2006,2007
Lake	17				
Lassen	18				
Los Angeles	19	2006,2007	2006	2006,2007	2006,2007
Madera	20	2006,2007		2006,2007	2006,2007
Marin	21	2006,2007			
Mariposa	22	2006,2007			
Mendocino	23				
Merced	24	2006,2007			2006,2007
Modoc	25				
Mono	26			2006,2007	
Monterey	27				
Napa	28	2006,2007			
Nevada	29	2006,2007			

Data obtained from the EPA Greenbook (USEPA, 2009b)

Blanks cells indicate that county was in attainment for the criteria pollutant during the study timeframe. Otherwise, the year of non-attainment for the study timeframe is provided.

California Counties by Attainment Status (2006-2007) cont.

County Name	ccode	8hrO3ATT	COATT	PM10ATT	PM25ATT
Orange	30	2006,2007	2006	2006,2007	2006,2007
Placer	31	2006,2007			
Plumas	32				
Riverside	33	2006,2007	2006	2006,2007	2006,2007
Sacramento	34	2006,2007		2006,2007	
San Benito	35				
San Bernardino	36	2006,2007	2006	2006,2007	2006,2007
San Diego	37	2006,2007			
San Francisco	38	2006,2007			
San Joaquin	39	2006,2007		2006,2007	2006,2007
San Luis Obispo	40				
San Mateo	41	2006,2007			
Santa Barbara	42				
Santa Clara	43	2006,2007			
Santa Cruz	44				
Shasta	45				
Sierra	46				
Siskiyou	47				
Solano	48	2006,2007			
Sonoma	49	2006,2007			
Stanislaus	50	2006,2007		2006,2007	2006,2007
Sutter	51	2006,2007			
Tehama	52				
Trinity	53				
Tulare	54	2006,2007		2006,2007	2006,2007
Tuolumne	55	2006,2007			
Ventura	56	2006,2007			
Yolo	57	2006,2007			
Yuba	58				

Data obtained from the EPA Greenbook (USEPA, 2009b)

Blanks cells indicate that county was in attainment for the criteria pollutant during the study timeframe. Otherwise, the year of non-attainment for the study timeframe is provided.

VITA

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Major Field: Environmental Science

Scope and Method of Study:

This study focused on publicly available data from aerobic capacity and body composition testing in school children during 2006 and 2007 and assessed the relationship between physical fitness rates in California schools and those criteria pollutants that were identified as being in non-attainment during this time period. Fitness data were adjusted for several demographic variables that may influence overall physical fitness. A series of t-tests were conducted to determine if physical fitness differs between attainment and non-attainment areas. Both t-tests and one-way ANOVA were used to identify explanatory variables. Multivariate regression models were used to evaluate the strength of the association between fitness achievement and attainment status after controlling for demographic variables such as gender, socioeconomic status, grade, and ethnicity. For those pollutants that were found to be significant after controlling for demographic variables, additional analyses were performed to determine if a dose-response type relationship exists.

Findings and Conclusions:

Decreases in athletic performance and increased body fat levels in children could be predictive of the potential for adult illnesses. The results of this study suggest that certain criteria air pollutants may adversely influence the physical fitness of children. When properly adjusted for a number of associated confounders, the results of this study support the hypothesis that increases in ambient air pollutant concentrations are associated with decreased aerobic capacity and increased body fat in California schoolchildren. Schools located in non-attainment counties for carbon monoxide, 8-hour ozone, and PM_{10} had lower percentages of children passing aerobic capacity fitness testing than did schools located in attainment counties. $PM_{2.5}$ attainment status was not significantly associated with aerobic capacity passing rates. Passing rates for body composition testing were lower in schools located in non-attainment zones for all criteria air pollutants (CO, 8-hour O_3, PM_{10}, $PM_{2.5}$) evaluated in this study. Although the study design does not allow for causal determination of this relationship, further evaluation showed that a significant dose-response type relationship with aerobic capacity passing rates was present for 8-hour ozone. This association was found for both the number of days that 8-hour ozone concentrations exceeded the NAAQS in the year preceding fitness testing and the annual average concentration of ozone in the year preceding fitness testing. No dose-response type relationship was observed for aerobic capacity passing rates with varying levels of PM_{10}.

This study found that gender, grade, socioeconomic status, and ethnicity were significantly associated with both aerobic capacity and body composition passing rates. Body fat was also a significant factor for aerobic capacity passing rates. These variables, with the exception of ethnicity, each contributed more to the explanation of variance in the multiple regression models than did the attainment status of the criteria air pollutants that were evaluated.

ADVISER'S APPROVAL: Dr. Dee Ann Sanders